Fuzzy Assisted Handoff Algorithm for Micro and Macro Cellular System

A thesis submitted in partial fulfilment of the requirements for the degree of

Master of Technology

in

Telematics & Signal Processing

By

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CERTIFICATE

This is to certify that the thesis titled "**Fuzzy Assisted Handoff Algorithm for Micro and Macro Cellular System",** submitted by **Pragyana Patnaik**, Roll No. **208EC113** in partial fulfillment of the requirements for the award of the degree of **Master of Technology** in Electronics & Communication Engineering with specialization in Telematics and Signal Processing**,** to National Institute of Technology, Rourkela is an authentic work carried out by him under my supervision and guidance.

To the best of my knowledge, the matter embodied in the thesis has not been submitted to any other University / Institute for the award of any Degree or Diploma.

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List of Acronyms

ANFIS	Adaptive neuro fuzzy inference system
BS	Base Station
COA	Centre of area
CCI	Co-channel Interference
CDMA	Code division multiple access
1G	First generation
4G	Fourth generation
FDMA	Frequency division multiple accesses
FLS	Fuzzy logic system
GUI	Graphical user interface
HHO	Hard handoff
HMIP	Hierarchical Mobile IP
IMT	International Mobile Telecommunications
LOS	Lline of sight
MAHO	Mobile Assisted Handoff
MS	Mobile Station
MSC	Mobile Switching Centre
MTSO	Mobile Telephone Switching Office
MT	Mobile Terminal
NCHO	Network Controlled Handoff
NLOS	Non line of sight
QOS	Quality of service

RSS	Received Signal Strength
2G	Second generation
SHO	Soft handoff
3G	Third generation
TDMA	Time division multiple accesses

Abstract

Handoff is an essential part of any Mobile Communication Network. Efficient handoff algorithms provide cost-effective way for enhancing the capacity and QOS of cellular system. The work reported here in presents multi-criteria based hard handoff algorithm for micro and macro-cellular architecture. Fuzzy technique has been used as optimization engine. The fuzzy handoff algorithm based on Received Signal Strength (RSS), absolute threshold value, hysteresis level, slope ratios and speed of Mobile Terminal (MT) have been previously developed for conventional cellular networks. In this work the handoff algorithm has been improved by considering two new parameter, signalling delay and angle of motion of MT along with velocity as our input criteria. Two fuzzy models named Mamdani and Sugeno have been used for processing the input criteria. Further, ANFIS has also been used to tune the Sugeno model for parameter adjustment. The proposed fuzzy inference scheme uses triangular and trapezoidal membership function for fuzzification. The types of defuzzification method used are centriod and weighted average formula for Mamdani and Sugeno model respectively. Extensive simulation analysis has been used to validate the proposed technique. The results show that fuzzy is a viable option for handoff.

Chapter-1
Introduction

1.1 Introduction

Handoff is one of the key operations in cellular mobile communication systems. It is the means through which the continuity of a call is maintained when Mobile Terminal (MT) coverage moves from one cell area to another. Handoff can be defined as the process of transferring a mobile station from one base station or channel to another. The channel change due to handoff occurs through a change in time slot, frequency band, codeword, or a combination of these. In time division multiple accesses (TDMA) it occurs through a change in time slot. Where as in case of frequency division multiple accesses (FDMA) and code division multiple accesses (CDMA) it is achieved by frequency change and code change respectively. Efficient handoff algorithms preserve and enhance the capacity and quality of service (QOS) of communication systems. It is necessary to ensure that handoff should be performed reliably and without disruption to any calls. Failing which, leads to dropped calls and customer dissatisfaction. Thus it is necessary to revive the handoff issues in cellular mobile systems. The process of handoff can be divided into three stages: decision stage, planning stage and execution stage. In the decision stage, predefined matrices parameters are measured by mobile unit to determine whether handoff should be initiated. In planning stage, the necessary resource (e.g. available bandwidth) in the candidate base station that the mobile unit would be handed over to is checked and assigned to the mobile unit. In the execution stage, connection is transferred from the serving base station to candidate base station and the appropriate protocols are performed.

The work reported here focuses on the decision stage of handoff process. Many of the existing handoff algorithms do not exploit the advantage of multi-criteria handoff, which can provide better performance than single criterion algorithms. This is due to the flexible and complementary nature of handoff criteria. A fuzzy based multi-criteria handoff algorithm is proposed as a solution to handoff decision. Following are the reasons for using fuzzy system:

[A] Fuzzy systems are conceptually easy to understand; [B] it brings in intelligence in the system; [C] Fuzzy system has been implemented in many engineering application with a considerable success; [D] Fuzzy system are simple and hence easy to implement in hardware.
Handoff with fixed parameters cannot perform well in different system environment. Specific characteristics of the communication system should be taken into account while designing a handoff algorithm. Recently, the use of link layer information for handoff detection has [1] [2] [3], Signalling delay of handoffs mainly depends on traffic load in the network and distance between user and its home network. So designing handoff algorithms with fixed signalling delay can suffer from poor performance when the handoff signalling delay varies. The existing link-layer assisted handoff algorithms do not consider the influence of user's speed on the performance of handoff. An attempt has been made to address this issue.

Fuzzy logic based techniques for handoff in cellular communication has been reported in [4] - [5]. The handoff criteria use threshold values to membership functions. The possible weakness in [4] and [6] is the jump values inherent in some fuzzy sets and takes only non line of sight (NLOS) transmission into consideration. The fuzzy sets chosen in this work have smooth membership function that increases or decreases gradually. Handoff techniques in cellular networks are reported briefly in literature review of Chapter-2.

In our new handoff decision algorithm the handoff decision matrices are, velocity of the MT which we consider positive for moving away and negative for approaching the serving BS, signalling delay and angle of motion of MT. We use Mamdani and Sugeno fuzzy inference system to process these matrices parameters. The output of our FIS is the membership value of handoff. Considering the threshold for handoff as 0.5 we plot the probability of false handoff and handoff failure. Our tests for the studied case have shown that the handoff increases with increasing velocity of MT and signalling delay. There is a significant decrease in false handoff initiation probability as compared to analytical results. From the results it was observed that the false handoff initiation probability and handoff failure probability increase with increase the cell radius. The output surface plot of Sugeno model clearly specify inter and intra system handoff. ANFIS is applied to Sugeno model to tune the parameter and to make the model adaptive. The error shown after training is satisfactory. The output with training and testing data were also presented.

1.2 Cellular Concept

The cellular concept is the idea of replacing large, single high power transmitter cells with several small, low power transmitter cells. Each of these cells typically provides coverage to a small portion of the coverage area. This effectively solved the problem of limited user capacity and spectral congestion by frequency reuse. This permits high capacity in a limited spectral allocation without any major system overhauls [7]. A base station transmitter at the centre of the cell is assumed to service all the mobile stations within the cell area. This can be seen in Figure-1.1. Some of the terminology used in cellular communications is explained below:

Mobile Station (MS): The mobile station is intended for use while in motion at an unspecified location.

Base Station (BS): The base station is a fixed station used for radio communication with MS.

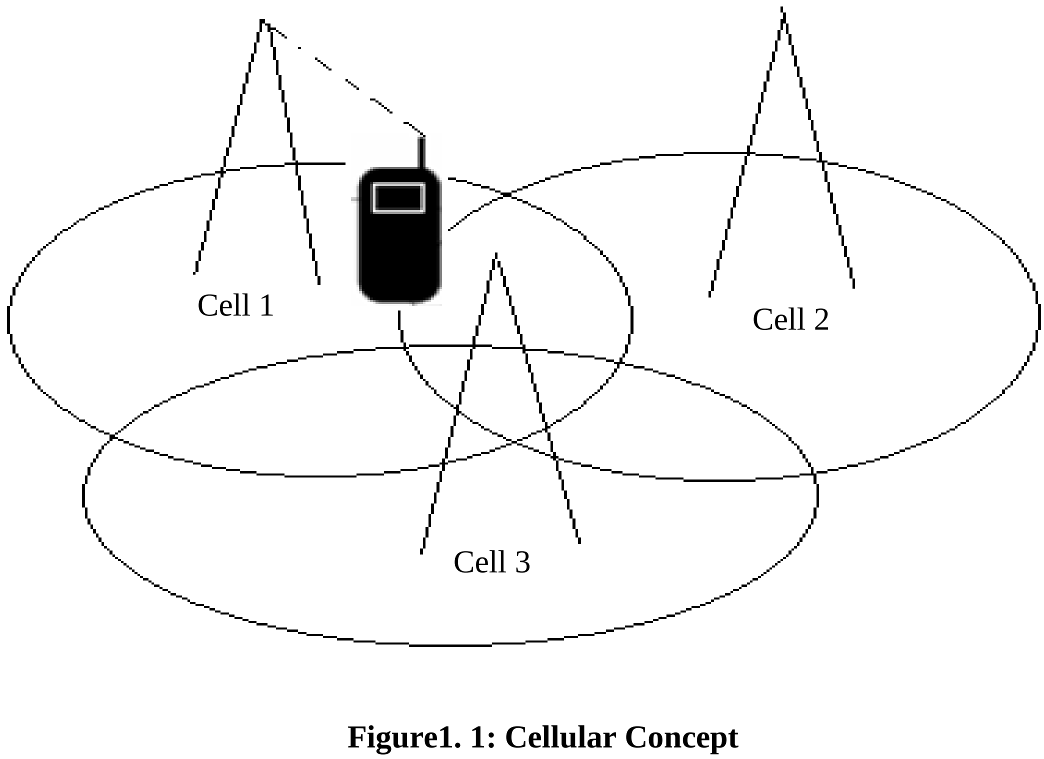

Figure1. 1: Cellular Concept

Mobile Switching Centre (MSC): The mobile switching centre coordinates the routing of calls in a large service area. It is also referred to as the Mobile Telephone Switching Office (MTSO).

Forward Channel: The forward channel is the radio channel used for the transmission of information from the base station to the mobile station. It is also known as the downlink.

Reverse Channel: The reverse channel is the radio channel used for the transmission of information from the mobile station to the base station. It is also known as the uplink.

Handoff: Handoff is a process of transferring a mobile station from one base station or channel to another. The channel change due to handoff occurs through a time slot for time division multiple access (TDMA), frequency band for frequency division multiple access (FDMA), and codeword for code division multiple access (CDMA) systems.

Co-channel Interference (CCI): The co channel interference is caused when the signal of the specified cell is corrupted due to another signal in remote cell using the same frequency or channel.

The following phases are involved in the planning of cellular communications:

- Assessment of traffic density;
- Determination of cell sizes and capacity;
- Decisions about unidirectional or sectored cells and antenna directions;
- Selection of best BS sites to cover the required area;
- Frequency allocation;
- Choice of power control parameters; and
- Selection of handoff parameters.

1.3 Cellular Wireless Standards [8]

Cellular wireless standard can be broadly divided into four categories, i.e. first generation (1G), second generation (2G), third generation (3G) and fourth generation (4G) respectively. The first generation (1G) wireless communications system use frequency division multiple access (FDMA) as the multiple access technology. FDMA is an analog transmission technique that is inherently narrowband. The individual calls used different frequencies and share the available spectrum through FDMA. The radio interface technology of the first generation wireless cellular system is tabulated in Table-1. The handoff process in 1G wireless communication system is Network Controlled Handoff (NCHO). Currently 1G systems are not in operation.

Table 1: First Generation Analog Cellular Systems

Region	America	Europe	Japan
Parameter	AMPS	ETACS	NTT
Multiple access	FDMA	FDMA	FDMA
Duplexing	FDD	FDD	FDD
Forward channel	869-894 MHz	935-960 MHz	870-885 MHz
Reverse Channel	824-849 MHz	890-915 MHz	924-940 MHz
Channel spacing	30 kHz	25 kHz	25 kHz
Data rate	10 kbps	8 kbps	0.3 kbps
Spectral efficiency	0.33 bps/Hz	0.33 bps/Hz	0.012 bps/Hz
Capacity	832 channels	1000 channels	600 channels

The second generation (2G) wireless systems use digital transmission. The multiple access technology is both time division multiple access (TDMA) and code division multiple access (CDMA). Although the second generation cellular systems offer higher transmission rates with greater flexibility then the first generation systems, they are nevertheless narrowband system. The digital technology allows greater sharing of the radio hardware in the base station among the multiple users, and provides a large capacity to support more users per base station per MHz of spectrum than analog systems. The radio interface technology of the second generation digital systems is tabulated in Table-2. Mobile Assisted Handoff (MAHO) process is used in 2G wireless Communication System.

The service offered by both 1G and 2G systems is predominantly voice. The third generation (3G) standard is based on CDMA as the multiple access technology. With transmission rate of up to 2Mbps, 3G systems are wideband, and are expected to support multimedia services.

Today's 3G systems can in practice offer up to 14.0 Mbps on the downlink and 5.8 Mbps on the uplink. International Mobile Telecommunications-2000 (IMT-2000), better known as 3G or 3rd Generation. 3G networks offer greater security than their 2G predecessors. An overview of 3G/IMT-2000 standards is tabulated in Table-3. 3G systems are also used MAHO process for Handoff.

Table 2: Second Generation Digital Cellular System

Region	U.S.	Europe	Japan	U.S.
Parameter	IS-54	GSM	PDC	IS-95
Multiple access	TDMA/FDD	TDMA/FDD	TDMA/FDD	CDMA
Modulation	$\pi/4$ DQPSK	GMSK	$\pi/4$ DQPSK	QPSK/OQPSK
Forward channel	869-894 MHz	935-960 MHz	810-826 MHz	869-894 MHz
Reverse Channel	824-849 MHz	890-915 MHz	940-956 MHz	824-849 MHz
Channel spacing	30 kHz	200 kHz	25 kHz	1,250 kHz
Data /chip rate	48.6 kbps	270.833 kbps	42 kbps	1.2288 Mbps
Speech codec rate	7.95 kbps	13.4 kbps	6.7 kbps	1.2/2.4/4.8/9.6 kbps

4G refers to the IMT advanced/ fourth generation of cellular wireless standards. It is a successor to 3G and 2G standards. Technologies considered to be early 4G include: Flash-OFDM, the 802.16e mobile version of Wi-Max (also known as Wi-Bro in South Korea), and HC-SDMA. The nomenclature of the generations generally refers to a change in the fundamental nature of the service. The first was the move from analogue (1G) to digital (2G) transmission. This was followed by multi-media support, spread spectrum transmission and at least 200 kbps (3G) and now 4G, which refers to all IP packet-switched networks, mobile ultra-broadband (gigabit speed) access and multi-carrier transmission. A 4G system is expected to provide a comprehensive and secure all-IP based solution where facilities such as

IP telephony, ultra-broadband Internet access, gaming services and streamed multimedia may be provided to users.

Table 3: Overview of 3G / IMT-2000 Standards

ITU IMT 2000	Common names		Bandwidth of data	Pre 4G	duplex	channel	description	Geographical areas
TDMA single carrier (IMT-SC)	EDGE (UWT-136)		EDGE Evolution	NONE	FDD	TDMA	Evolutionary upgrade to GSM/GPRS	World wide except Japan and south Korea
CDMA multi carrier (IMT-MC)	CDMA2000		EV-DO	UMB		CDMA	Evolutionary upgrade to CDMA one (IS-95)	Americas, Asia's, some other
CDMA direct spread (IMT_DS)	UMTS	W-CDMA	HSPA	LTE			Family of revolutionary standard	World wide
CDMA-TDD (IMT-TC)		TD-CDMA			TDD			Europe
		TD-SCDMA						china
FDMA/TDMA (IMT-FT)	DECT		none			FDMA/TDMA	Short-range, standard for cordless phone	Europe, USA
IP-OFDMA			WIMAX (IEEE 802.16)			OFDMA		World wide

1.4 Thesis Outline

This section outlines the thesis layout. This thesis is organised into seven chapters. Following this introduction; Chapter-2 reviews in brief the overview of handoff in cellular mobile communication systems. Chapter-3, discusses fuzzy logic, Mamdani and Sugno inference engine and Adaptive neuro fuzzy inference system (ANFIS). Chapter-4 we describes the proposed algorithm and its design procedure. Chapter-5 analyzes the performance of Mamdani and Sugeno fuzzy handoff performance is analyzed. Anfis is used for learning and model validation. Finally, Chapter-6 presents the concluding remarks and future work.

Chapter-2
Cellular Handoff Fundamentals

2.1 Introduction

This chapter presents various aspects of handoff and discusses handoff related features of cellular systems. Desirable features of handoff are highlighted, and complexities of handoff are described. Handoff criteria's, conventional handoff algorithms and emerging handoff algorithms are discussed.

2.2 Cellular Handoff Fundamentals

Handoff is the key operation in cellular mobile communication systems. It is the means through which the continuity of a call is maintained when MT moves from one cell area to another. Handoff can be defined as the process of transferring a mobile station from one base station or channel to another. The channel change due to handoff occurs through a change in time slot, frequency band, codeword or a combination of these. In time division multiple access (TDMA) time slot is changed. Where as in frequency division multiple access (FDMA) frequency is changed and code division multiple access (CDMA) code is changed. Efficient handoff algorithms cost-effectively preserve and enhance the capacity and quality of service (QOS) of communication systems.

Figure-2.1 shows a simple handoff scenario in which a Mobile Station (MS) travels from Base Station (BS) A to BS B. Initially, the MS is connected to BS A. The overlap between the two cells is the handoff region in which the mobile may be connected to either BS A or BS B. At a certain time during the travel, the mobile is handed off from BS A to BS B. When the MS is close to BS B, it remains connected to BS B. The process of handoff has to be completed in the overlap region.

The process of handoff can be divided into three stages: the decision stage, the planning stage and the execution stage. In the decision stage, predefined link quality metrics are measured by the network elements or by the mobile unit to decide whether the handoff should be initiated. In the planning stage, the necessary resource (e.g., the available bandwidth) in the candidate base station that the mobile unit would be handed over to is checked and assigned to the mobile unit if the channel capacity is available. In the execution stage, the connection is transferred from the original serving base station to the candidate base station, and the appropriate protocols are performed. Handoff algorithms normally operate in the first phase of handoff process.

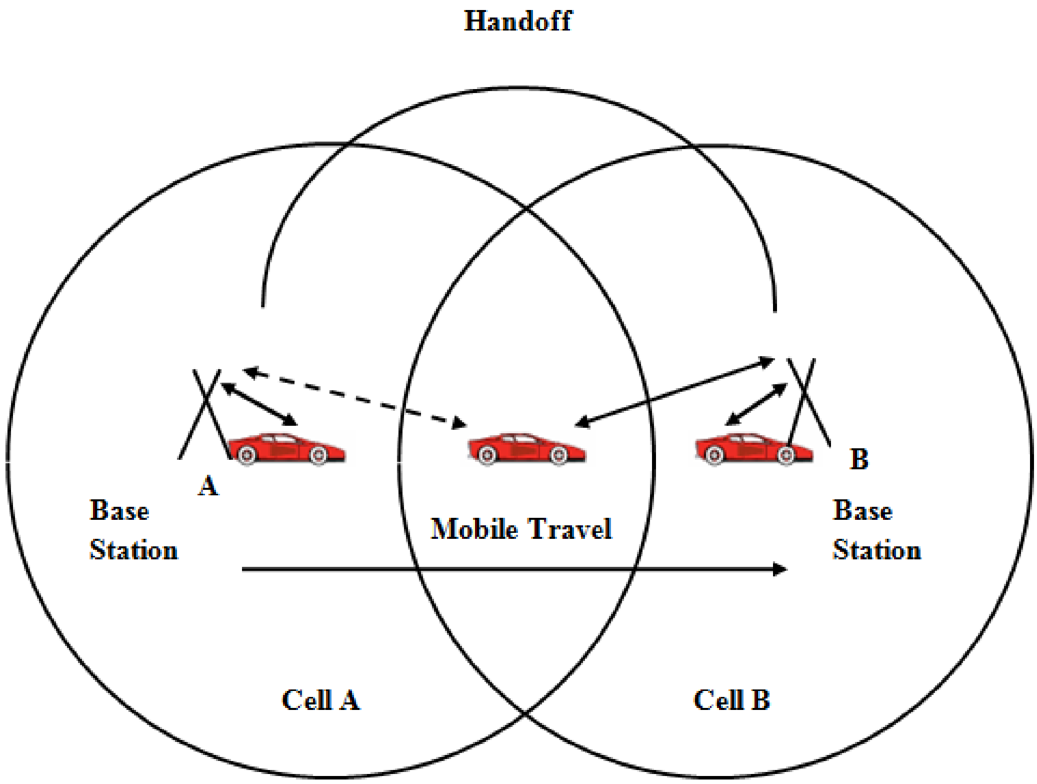

Figure 2. 1: Handoff Scenarios in Cellular System

2.3 Types of Handoff

Handoffs are broadly classified into two categories—hard and soft handoffs. Hard handoff (HHO) is ‘break before make," meaning that the connection to the old BS is broken before a connection to the candidate BS is made. HHO occurs when handoff is made between disjointed radio systems, different frequency assignments or different air interface characteristics or technologies [9]. Usually, the hard handoff can be further divided into two different types—intracellular and intercellular handoffs. A handoff made within the currently serving cell (e.g., by changing the frequency) is called an intracellular handoff. A handoff made from one cell to another is referred to as an intercellular handoff. Soft handoff (SHO) is “make before break," meaning that the connection to the old BS is not broken until a connection to the new BS is made. In fact, more than one BS is normally connected simultaneously to the MS. There are different types of SHO. When sectors of the same BS are involved in communication with the MS, the handoff is called softer handoff. When one sector from each BS is involved, the handoff is called soft handoff. When multiple sectors of one BS and one or more sectors of another BS communicate with the MS, the resulting SHO is called softer-soft handoff. Mobility in network is managed by two different handoff strategies, namely Horizontal Handoff and Vertical Handoff. In case of Horizontal Handoff, handoff is between two network access points or base stations that use the same wireless network access technology. The handoff is purely due to mobility of the mobile station. In case of Vertical Handoff, handoff is between two network access points or base stations that use the different wireless network access technology.

2.4 Handoff Initiation

We define following notation with reference to Figure-2.2, which shows handoff from current base station (BS) referred as BS1 to a new base station referred as BS2.

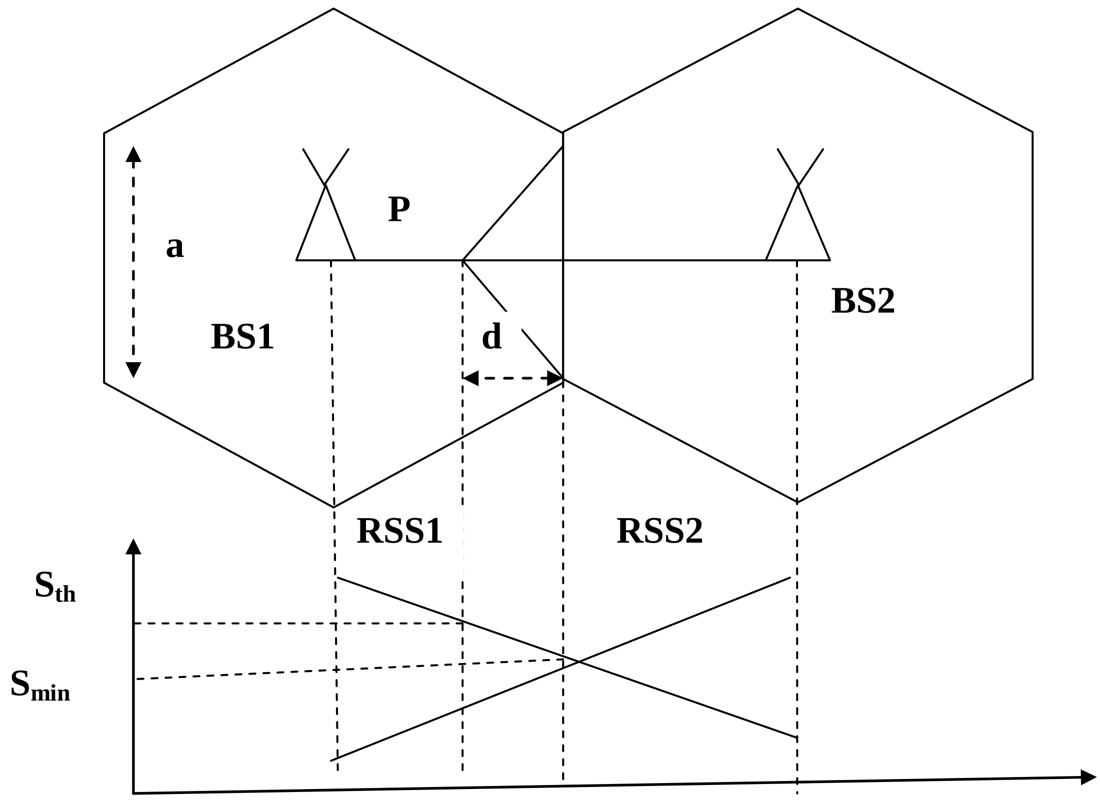

Figure2.2: Analysis of Handoff Process

S_{min}: It is the minimum Received signal strength (RSS) for acceptable voice quality for communication between Mobile Terminal (MT) and BS1.

S_{th}: The threshold value of RSS to initiate handoff. Therefore when RSS of BS1 drops below S_{th} the MT initiate handoff to new base station i.e. BS2.

$\Delta = S_{th} - S_{min}$: This margin is called Δ should not be very large (for unnecessary handoff) or too small (leading to call drop due to weak signal before handoff is completed).

During the course of movement, the MT discovers that it is going to move into the coverage area of the BS2 and hence needs to perform hierarchical Mobile IP (HMIP) registration with the BS2. The MT may learn about the possibility of moving into another cell when the RSS of BS1 decreases continuously. Once the MT discovers that it may enter into the coverage area of the BS2, the next challenge is to decide the right time to initiate HMIP registration procedures with the BS2. The existing link-layer-assisted HMIP protocols propose to initiate the HMIP registration when the RSS from the serving BS, e.g., BS1 in Figure-2.2 drops below a fixed threshold value (S_{th}). Below, we analyze the performance of these solutions. We assume that, during the course of its movement, when the MT reaches the point P (the distance of P from the cell boundary is d) as shown in Figure-2.2, the RSS from the BS1 drops below S_{th}. Therefore, when the MT reaches P, it initiates the HMIP registration with the BS2. At this point, the RSS received by the MT from BS2 shown as RSS2 in Figure-2.2 may not be sufficient for the MT to send the HMIP registration messages to BS2. Hence, the MT may send the HMIP registration messages to BS2 through BS1. This is called preregistration [3]. For a smooth and successful handoff from BS1 to BS2, MT's HMIP registration with BS2 and link and MAC layer associations with BS2 must be completed before the RSS of BS1 drops below S_{min}, i.e., before the MT moves beyond the coverage area of BS2.

2.5 Features of Handoff

An efficient handoff algorithm can achieve many desirable features by trading different operating characteristics. A list of desirable features of handoff algorithms are described below [10] [11] [12] [13] [14].

- Handoff should be fast so that the user does not experience service degradation or interruption. Service degradation may be due to a continuous reduction in signal strength or an increase in CCI adds to the network delay at the Mobile Switching .

Service interruption may be due to a “break before make" approach of HHO. Note that the delay in the execution of a handoff algorithm Centre (MSC) or Mobile Telephone Switching Office (MTSO). Fast handoff also reduces CCI since it prevents the MS from going too far into the new cell.

- Handoff should be reliable. This means that the call should have good quality after handoff. SIR and RSS help determine the potential service quality of the candidate BS.
- Handoff should be successful; a free channel should be available at the candidate BS. Efficient channel allocation algorithms and some traffic balancing can maximize the probability of a successful handoff.
- The effect of handoff on the quality of service (QoS) should be minimal. The quality of service may be poor just before handoff due to a continuous reduction in RSS, SIR, etc.
- Handoff should maintain the planned cellular borders to avoid congestion, high interference, and use of assigned channels inside the new cell. Each BS can carry only its planned traffic load. Moreover, there is a possibility of increased interference if the MS goes far into another cell site while still being connected to a distant BS because co channel distance is reduced and the distant BS tends to use a high transmit power to serve the MS.
- The number of handoffs should be minimized. Excessive handoffs lead to heavy handoff processing loads and poor communication quality, which may result following: (i) the more attempts at handoff, the more chances that a call will be denied access to a channel, resulting in a higher handoff call dropping probability, (ii) a lot of handoff attempts causes more delay in the MSC processing of handoff requests, which will cause signal strength to decrease over a longer time period to a level of unacceptable quality. Also, the call may be dropped if sufficient SIR is not achieved.
- Handoff requires network resources to connect the call to a new BS. Thus, minimizing the number of handoffs reduces the switching load. Unnecessary handoffs should be prevented; the current BS might be able to provide the desired service quality without interfering with other MSs and BSs.

2.6 Handoff Complexities

Several factors complicate the process of handoff. Some of these handoff complexities are briefly listed below:

Cellular structures and topographical features: There are different types of cellular system deployment scenarios. There could be big cells in rural or suburban areas (called macro cells), small cells in urban areas (called microcells) or an overlay system with a given area, both containing macro cells and microcells. The propagation environment is quite different in micro or macro cells. Large scale fading and small scale fading has large variations in urban microcells then in rural macro cells. Furthermore, in urban microcells effects such as street corner effect exists, are characterized by a sudden drop in signal strength over a short distance.

Traffic: Traffic distribution is a function of time and space. The handoff process should work well in different traffic scenarios. Examples of approaches to deal with traffic no uniformities include traffic balancing in adjacent cells, use of different cell sizes, no uniform channel allocation and dynamic channel allocation.

System constraints: Several systems have constraints over common characteristics, such as transmit power and propagation delay. The handoff process should consider such system constraints.

Mobility: The quality of communication link is influenced by the degree of mobility. A high speed MS moving away from a serving BS, experiences signal degradation faster than a low speed MS. Hence mobility plays an important role in the handoff process.

2.7 Handoff Decision

There are numerous methods for performing handoff, at least as many as the kinds of state information that have been defined for MSs, as well as the kinds of network entities that maintain the state information [15]. The decision-making process of handoff may be centralized or decentralized (i.e., the handoff decision may be made at the MS or network). From the decision process point of view, there are at least four different kinds of handoff decisions; network controlled handoff (NCHO), mobile assisted handoff (MAHO), soft handoff (SHO) and mobile controlled handoff (MCHO).

Table 4: Brief Overview of Handoff Protocol

	Types	**Example**	**Approximate time for completion of Handoff**
HARD HANDOFF	**Network Controlled Handoff (NCHO)** Here the Mobile Telephone Switching Office (MTSO) is responsible for overall handoff decision .MTSO measures the necessary RSS measurements.	1^{st} Generation cellular systems such as (AMPS) advanced mobile phone system	100-200 ms
	Mobile Assisted Handoff (MAHO) Here MS measure the RSS & send to the BS. Based on RSS BS or MSC takes handoff decision	2^{nd} and 3^{rd} Generation cellular system such as GSM,IS-54,IS-136,DAMPS	1 second
	Mobile Controlled Handoff (MCHO) Here BS & MS both involves in RSS measurement. MS decide when to initiate handoff based on RSS of BS and itself	Digital European Cordless Telephone (DECT),Mobile IP Networks	0.1 second
SOFT HANDOFF	In this process Mobile terminal (MT) is able to “talk” to more than one BS simultaneously. Not convenient for GSM ,or DAMPS	CDMA IS-95 Standard, WCDMA ,UMTS	

As the handoff decision making Process is decentralized (i.e., moving from NCHO to MCHO), handoff delay (i.e., the time required to execute a handoff request) decreases, but the measurement information available to make a handoff decision also decreases. These protocols are summarised in Table-4

2.8 Prioritization Schemes

One of the ways to reduce the handoff failure rate is to prioritize handoff. Handoff algorithms that try to minimize the number of handoff give poor performance in heavy traffic situations. In such situations, a significant handoff performance improvement can be obtained by prioritizing handoff. Two of the most important parameter for evaluating a handoff processes are forced termination probability and call blocking probability. An ideal handoff is one in which forced probability decreases while maintaining blocking probability. In non prioritization scheme new call and handoff calls are treated in same way, leading to increases in the forced termination probability. Prioritization scheme reduce the forced termination probability by assigning more channel to handoff calls. The two known prioritization schemes are: Guard channels and Queuing of handoff calls.

Guard channels:

In this scheme some of the total available channels in a cell are reserved for handoff calls only. Hence, less no of channels are available for originating call. This process increases the call blocking probability. However, Guard channel scheme provide better spectrum utilization under dynamic channel assignment strategies.

Queuing handoff:

Queuing schemes queues the handoff calls when all channels are occupied in a base station. When a channel is released it is assigned to one of the handoff calls in queue. Queuing is possible due to time interval between handoff initiation and receiver threshold. This scheme can be used with or without the guard channel scheme and does not provide any guarantee for zero forced termination probability.

2.9 Literature Review

A large number of handoff algorithms have been proposed in the literature and classified according to the metrics used to decide whether a handoff is necessary or not, where these metrics are monitored, and how these metrics are processed. Some of the metrics proposed are; signal strength [16], distance [10], signal to noise ratio [17], bit error rate [18], traffic load [19], word error indicator [11], quality indicator [11] and some combination of these [11] [12]. Metrics can be measured and processed on the network entity or on the mobile. There are several handoff decision algorithms that employ tools of artificial intelligence like fuzzy logic systems [20] [13], neural networks [20], [14], and pattern recognition algorithms [20], [21] [22] to process the collected metrics.

The Received Signal Strength (RSS) based handoff algorithm associates mobile host to the access point, which has the strongest perceived signal strength at the mobile host side. The signal received from an access point degrades as the distance between the mobile and the access point increases. However, this degradation is a random process due to uncertainties in the propagation environment. Around mid-point between two access points, the difference in the signal strengths received from access point 1 and access point 2 oscillates and the mobile may handoff several times between access point 1 and access point 2. This is called the ping-pong effect.

To remedy the ping-pong effect, a threshold is introduced to the received signal strength based handoff algorithm [23]. The mobile does not hand off as long as the received signal strength from the currently serving access point does not drop below the predetermined threshold level. This algorithm is called Absolute Signal Strength algorithm [20]. Another technique is to introduce a hysteresis to the RSS algorithm [23]. The mobile does not hand off to another access point while the received signal strength from the candidate access point is not better an amount of predetermined hysteresis level than the received signal strength of the currently serving access point. This algorithm is called Relative Signal Strength algorithm [20]. Introducing both hysteresis and threshold is called the combined absolute and relative signal strength algorithm [20]. Either introducing hysteresis or threshold reduces the ping-pong effect but introduces a delay to the handoff, i.e., handoff is done later than it is expected. Effects of delaying handoff are increased interference, lower grade of service, i.e., increased call blocking and dropping rates. There are studies that have optimized signal-strength based handoff algorithms by minimizing two conflicting design criteria, the handoff delay and the mean number of handoffs between access points [10] [12]. In the design of handoff algorithms, there is an inherent trade off in timeliness and accuracy. The algorithms, which we explained thus far, were signal strength based algorithms. Another category is the distance-based algorithms.

Distance-based algorithms relate the mobile with the closest access point [10]. The relative distance measurements can be obtained by comparing propagation delay times. Velocity adaptive handoff algorithms consider mobiles with different velocities, i.e., the handoff needs of fast moving mobiles should be determined immediately. This can be achieved by adjusting the effective length of the averaging window in which received signal strengths from the access point are averaged [15]. In direction biased algorithms handoffs to the access points towards which the mobile is moving are encouraged, while handoffs to the access points from which the mobile is receding is discouraged [20]. In pre-selection handoff algorithm, a mobile hands off to the access point towards which the mobile is moving even though measured handoff decision metrics of that access point is not the best. Considering that these metrics will improve as the mobile gets closer to the access point. However it is essentially complex to make handoff decision considering multiple criteria. Sometimes, the trade-off of some criteria should be considered. Therefore heuristic approaches based on Neural network (NN), Genetic algorithm (GA) and fuzzy logic (FL) can prove to be efficient for wireless networks.

Fuzzy logic systems and neural network classifiers are good candidates for pattern classifiers due to their non-linearity and generalization capability. When employing pattern recognition based algorithms, we have the overhead of obtaining the training data and actually pre-training the system. However, when the system is trained, we have the opportunity to employ multi-criteria algorithms and optimizing the handoff decision with conflicting criteria, i.e., handoff delay and number of handoffs. Some researchers have applied fuzzy logic theory in handoff process such as Kinoshita and Oku [24], Homnan and Benjapolakul [25], and Edwards et al. [26]. Kinoshita and Oku applied fuzzy logic for creating inference rules for softer decision but emphasizing on HHO in indoor areas. Homnan and Benjapolakul proposed HHO based on fuzzy inference. The signal strength that a mobile station receives from a base station and the distance between a mobile station and a base station are used as inputs, while the output is the handoff decision value. Edwards et al. [26] proposed two handoff techniques using fuzzy logic for microcellular HHO. The first algorithm uses an adaptive fuzzy predictor, while the second algorithm uses a fuzzy averaging technique. The results of [26] show that fuzzy is a viable option for microcellular HHO.

2.10 Conclusion

A high performance handoff algorithm can achieve many of the desirable features by making appropriate tradeoffs. However, several factors such as topographical features, traffic variations, propagation environments, and system-specific constraints complicate the task of handoff algorithms. Handoff algorithms with a specific set of parameters cannot perform uniformly well in different communication system deployment scenarios. These system structures are expected to co-exists in future wireless communication systems and warrant a substantial study. Handoff represents one of the radio resource management tasks carried out by cellular systems. Other resource management functions include admission control, channel assignment, and power control. If resource management tasks are treated in an integral manner, better overall performance can be obtained to achieve global goals by making appropriate tradeoffs.

Chapter-3
Fuzzy Logic SystemAnd ANFIS - An Introduction

3.1 Introduction

There are several tools of AI that help utilize human knowledge about the system to develop high performance systems. Some of the major AI tools are artificial neural network, fuzzy logic, and genetic algorithm and experts systems. This research exploits capability of fuzzy logic to develop adaptive intelligent handoff algorithms.

3.2 Introduction to Fuzzy Logic

Information can be represented by numbers or linguistic descriptions. For example, Temperature can be represented by the number 20 ^{0}F or by the linguistic description “Cold." The description “cold" is fuzzy and may represent any temperature between 10 ^{0}F and 30 ^{0}F, which can be called the fuzzy set (or fuzzy region) for the fuzzy variable temperature. Since humans usually think in terms of linguistic descriptions, giving these descriptions some mathematical form helps exploit human knowledge. Fuzzy logic utilizes human knowledge by giving the fuzzy or linguistic descriptions a definite structure.

A concise description of fuzzy logic theory is given next. First, basic concepts of fuzzy logic are introduced. These concepts are then utilized to explain a popular form of fuzzy logic system (FLS) that can serve as a building block in a system incorporating fuzzy logic. A comprehensive theory of fuzzy logic can be found in [27].

Fuzzy Set: Let U be a collection of objects and be called the universe of discourse. A fuzzy set $F \in U$ is characterized by a membership function $\mu_F(u)$: $U \rightarrow [0, 1]$ where $\mu_F(u)$ represents the degree (or grade) of membership of $u \in U$ in the fuzzy set F. Figure- 3.1 shows the membership functions of three fuzzy sets, “small," “medium," and “large," for a fuzzy variable SIR. The universe of discourse is all possible values of SIRs, i.e., U = [15, 25]. At an SIR of 19 dB, the fuzzy set “small" has the membership value 0.6.
Hence, $\mu_{small}(19) = 0{:}6$. Similarly, $\mu_{medium}(19) = 0{:}4$, and $\mu_{large}(19) = 0$.

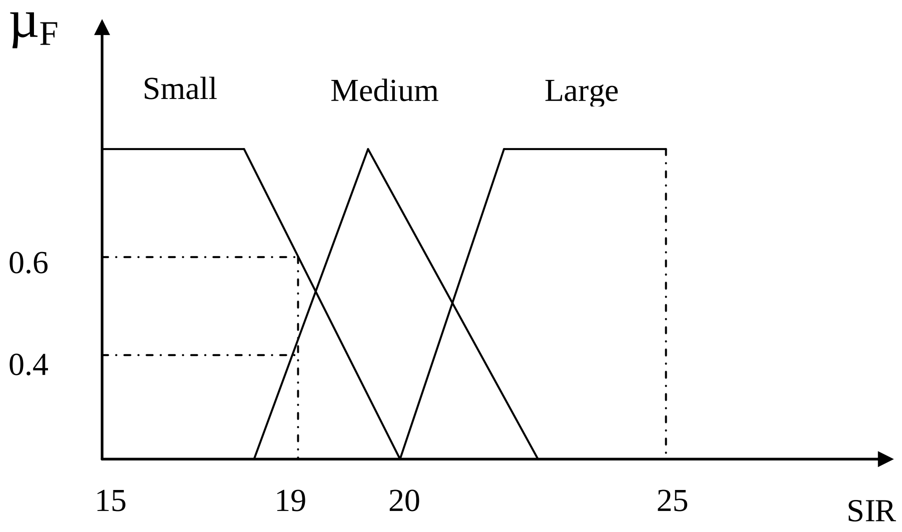

Figure 3. 1: An Example of Fuzzy Logic Membership Function

Support: The support of a fuzzy set F is the crisp set of all points $u \in U$ such that $\mu_F(u) > 0$.

Centre: The centre of a fuzzy set F is the point (or points) $u \in U$ at which $\mu_F(u)$ achieves its maximum value.

T-norm: A T-norm, denoted by *, is a two-place function from [0, 1] ×[0, 1] to [0, 1], which includes fuzzy intersection, algebraic product, drastic product, and bounded product, defined as

$$X * y = \min(x, y) \qquad \text{(fuzzy intersection)} \qquad (3.1)$$

$$X * y = xy \qquad \text{(algebraic product)} \qquad (3.2)$$

$$X * y = \begin{cases} x : y = 1 \\ y : x = 1 \\ 0 : x, y < 1 \end{cases} \qquad \text{(drastic product)} \qquad (3.3)$$

$$X * y = \max(0, x+y-1) \qquad \text{(bounded product)} \qquad (3.4)$$

Where $x, y \in [0, 1]$.

Fuzzy Relation: Let U and V be two universes of discourse. A fuzzy relation R is a fuzzy set in the product space U ×V, i.e., R has the membership function $\mu_R(u; v)$ where $u \in U$ and $v \in V$.

Sup-Star Composition: Let R and S be fuzzy relations in U ×V and V ×W; respectively. The sup-star composition of R and S is a fuzzy relation denoted by RoS and is given by

$$\mu_{RoS}(u, w) = \sup_{v \in V} [\mu_R(u, v) * \mu_S(v, w)] \quad (3.5)$$

Where $u \in U$, $w \in W$; and * could be any operator in the T-norm defended earlier. It is clear that RoS is a fuzzy set in U ×W.

Fuzzy Implications: Let A and B be fuzzy sets in U and V; respectively. A fuzzy implication, denoted by a → B, is a special kind of fuzzy relation in U × V with the following membership function:

$$\mu_{A \to B}(u, v) = \mu_A(u) * \mu_B(v) \quad (3.6)$$

This fuzzy implication is known as fuzzy conjunction. Other types of fuzzy implications are also available [27].

3.3 Fuzzy Inference System

Fuzzy inference systems (FISs) are also known as fuzzy rule-based systems, fuzzy model, fuzzy expert system, and fuzzy associative memory. This is a major unit of a fuzzy logic system. The decision-making is an important part in the entire system. The FIS formulates suitable rules and based upon the rules the decision is made. This is mainly based on the concepts of the fuzzy set theory, fuzzy IF–THEN rules, and fuzzy reasoning. FIS uses "IF. . . THEN" statements, and the connectors present in the rule statement are "OR" or "AND" to make the necessary decision rules. The basic FIS can take either fuzzy inputs or crisp inputs, but the outputs it produces are almost always fuzzy sets. When the FIS is used as a controller, it is necessary to have a crisp output. Therefore in this case de-fuzzification method is adopted to best extract a crisp value that best represents a fuzzy set. The whole FIS is discussed in detail in the following subsections:

3.3.1 Mamdani fuzzy inference system

Mamdani fuzzy inference method is the most commonly seen fuzzy methodology. Mamdani method was among the first control systems built using fuzzy set theory. It was proposed by Mamdani (1975) as an attempt to control a steam engine and boiler combination by synthesizing a set of linguistic control rules obtained from experienced human operators.

The components of the FIS proposed by Mamdani are fuzzifier, fuzzy rule base, fuzzy inference engine, and defuzzifier as shown in Figure-3.2. This configuration of the FIS has been widely used in industrial applications and consumer products. This FIS configuration has the following advantages compared to other FISs [27].

- This FIS has real-valued variables as its inputs and outputs, which is suitable for engineering applications where measured variables are real-valued and not fuzzy. (Pure FISs require fuzzy variables as inputs.)
- This FIS provides a common framework, a rule base, for incorporating fuzzy IF-THEN rules to exploit human knowledge.
- This FIS allows several degrees of freedom in the selection of different components of the FIS.
- This FIS allows fusion of numerical information and linguistic information. For example, numerical information (e.g., measurements) can be used to train the FIS to derive an adaptive FIS.

The components of the Mamdani FIS are described next.

Fuzzifier: The fuzzifier maps a crisp point, $x = [x1, x2, xn]^T \in U$, into a fuzzy set A' in U. Two choices for the fuzzifier forms are singleton fuzzifier and non-singleton fuzzifier.

Singleton Fuzzifier: A' is a fuzzy singleton with support x, i.e., $\mu_{A'}(x') = 1$ for $x' = x$ and $\mu_{A'}(x') = 0$ for all other $x' \in U$ with $x' \neq x$.

Non-singleton Fuzzifier: For this fuzzifier, $\mu_{A'}(x') = 1$, and $\mu_{A'}(x')$ decreases from 1 as x' moves away from x. For example, $\mu_{A'}(x') = \exp(-(x'-x)^T (x'-x)/\sigma^2)$ where σ is a parameter characterizing the shape of $\mu_{A'}(x')$ and T is a transpose operation.

Fuzzy Rule Base: A fuzzy rule base consists of a collection of fuzzy IF-THEN rules. A typical form is shown here:

$$R^{(l)}: \text{IF } x_1 \text{ is } F_1^l \text{ and ... and } x_n \text{ is } F_n^l, \text{ THEN } y \text{ is } G^l \quad (3.7)$$

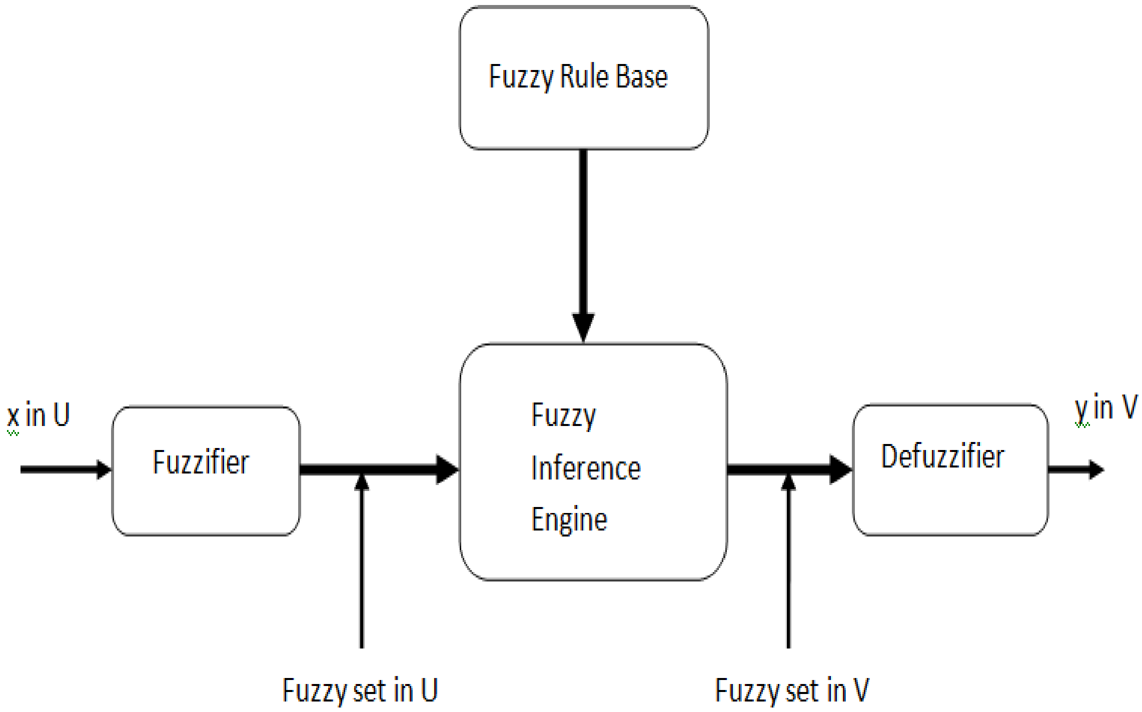

Figure 3. 2: An Example of Fuzzy Inference System

Where F_i^l and G^l are fuzzy sets in $U_i \subset R$ and $V \subset R$, respectively, and where $x = [x1, x2, xn]^T \in U_1{\times}U_2{\times}{:}\ {\times}UN$ and $y \in V$ are linguistic variables. Here, l ranges from 1 to M with M representing the total number of rules.

Let a fuzzy rule be expressed as “IF X is A, then Y is B" where X is the input fuzzy variable, Y is the output fuzzy variable and A, B are corresponding fuzzy (linguistic) sets. A and B can be “small" and “big" respectively. The “IF" clause of the rule is called the antecedent and the “THEN” clause the consequent Each antecedent and consequent in a fuzzy logic rule forms a membership function that can be of different shapes, triangular and Gaussian shapes being more popular. Each input or output fuzzy variable has a membership degree of unity at the centre value of the corresponding fuzzy set. Assume that the support of the fuzzy set A is between ten and thirty, and that twenty is the centre value of the membership function for the fuzzy set A. Then, the input fuzzy variable X has a membership degree of unity with set A when X is twenty.

Fuzzy Inference Engine: In the fuzzy inference engine, fuzzy logic principles are used to combine the fuzzy IF-THEN rules in the fuzzy rule base, and fuzzy sets in $U = U_1 \times U_2 \times ::: \times Un$ are mapped into fuzzy sets in V.

A fuzzy rule is interpreted as a fuzzy implication $F_1^l \times : \times F_n^l \rightarrow G^l$ in $U \times V$. Let a fuzzy set $A' \in U$ be the input to the fuzzy inference engine. Then, each fuzzy IF-THEN rule determines a fuzzy set $B^l \in V$ using the sup-star composition:

$$\mu_{B^l}(U, w) = \sup_{x \in U} [\mu_{F_1^l \times \ldots \times F_n^l \rightarrow G^l}(x, y) * \mu_{A'}(x)] \tag{3.8}$$

Let $F_1^l \times : \times F_n^l = A$ and $G^l = B$.

There are different interpretations for a fuzzy implication, and there are different T-norms as defined earlier. Hence, the above equation can be interpreted in a number of ways. One interpretation, called the product-operation rule, is shown here:

$$\mu_{A \rightarrow B} (u, v) = \mu_A(x) * \mu_B(y). \tag{3.9}$$

This interpretation follows from the fuzzy conjunction implication by using the algebraic product for *.

Overall mapping of the fuzzy inference engine is described next. For an input A' (a fuzzy set in U), the output of the fuzzy inference engine can take two forms: (1) M fuzzy sets B' (l = 1,2, ...M) as in Eq. 3.8 with each one determined by one fuzzy IF-THEN rule as in Eq. 3.7, (2) one fuzzy set B', which is the union of the M fuzzy sets B^l. Thus,

$$\mu_{B'}(y) = \mu_{B^l}(y) \cup \ldots \ldots \cup \mu_{B^M}(y). \tag{3.10}$$

Defuzzifier: The defuzzifier maps fuzzy sets in V into a crisp point, $y \in V$. One of the choices for the defuzzifier is centre average defuzzifier, defined as

$$y = \frac{\sum_{l=1}^{M} \bar{y}^l \left(\mu_{B^l}(\bar{y}^l) \right)}{\sum_{l=1}^{M} \left(\mu_{B^l}(\bar{y}^l) \right)} \tag{3.11}$$

Where $\bar{y}^l$ is the centre of the fuzzy set G^l, i.e., the point in V at which $\mu_{G^l}(y)$ achieves its maximum value, and $\mu_{B^l}(\bar{y}^l)$ is given by Eq. 3.5. An example of a Mamdani inference system is shown in Figure-3.3

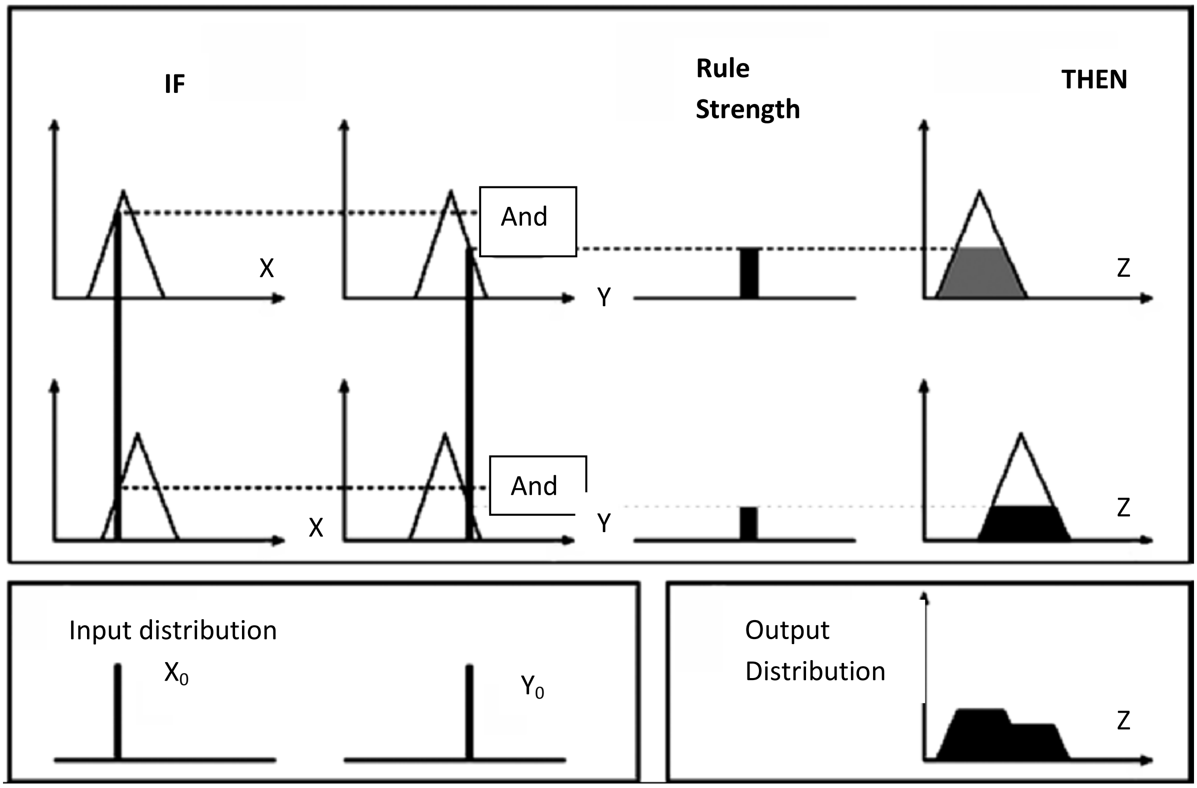

Figure 3. 3: A Two Input Two Rule Mamdani FIS with a Fuzzy Input

3.3.2 Sugeno Fuzzy System

The Sugeno fuzzy model was proposed by Takagi, Sugeno, and Kang in an effort to formalize a system approach to generating fuzzy rules from an input–output data set. Sugeno fuzzy model is also known as Sugeno–Takagi model. This FIS configuration has the following advantages.

- It is computationally efficient.
- It works well with linear techniques (e.g., PID control).
- It works well with optimization and adaptive techniques.
- It has guaranteed continuity of the output surface.
- It is well suited to mathematical analysis.

A typical fuzzy rule in a Sugeno fuzzy model has the format

$$\text{IF } x \text{ is } A \text{ and } y \text{ is } B \text{ THEN } z = f(x, y),$$

Where AB are fuzzy sets in the antecedent; Z = f(x, y) is a crisp function in the consequent. Usually f(x, y) is a polynomial in the input variables x and y, but it can be any other functions that can appropriately describe the output of the output of the system within the fuzzy region specified by the antecedent of the rule. When f(x, y) is a first-order polynomial, we have the first-order Sugeno fuzzy model. When f is a constant, we then have the zero-order Sugeno fuzzy model, which can be viewed either as a special case of the Mamdani FIS where each rule's consequent is specified by a fuzzy singleton, or a special case of Tsukamoto's fuzzy model where each rule's consequent is specified by a membership function of a step function cantered at the constant. Moreover, a zero-order Sugeno fuzzy model is functionally equivalent to a radial basis function network under certain minor constraints.

The first two parts of the fuzzy inference process, fuzzifying the inputs and applying the fuzzy operator, are exactly the same. The main difference between Mamdani and Sugeno is that the Sugeno output membership functions are either linear or constant. A Sugeno rule operates as shown in Figure-3.4.

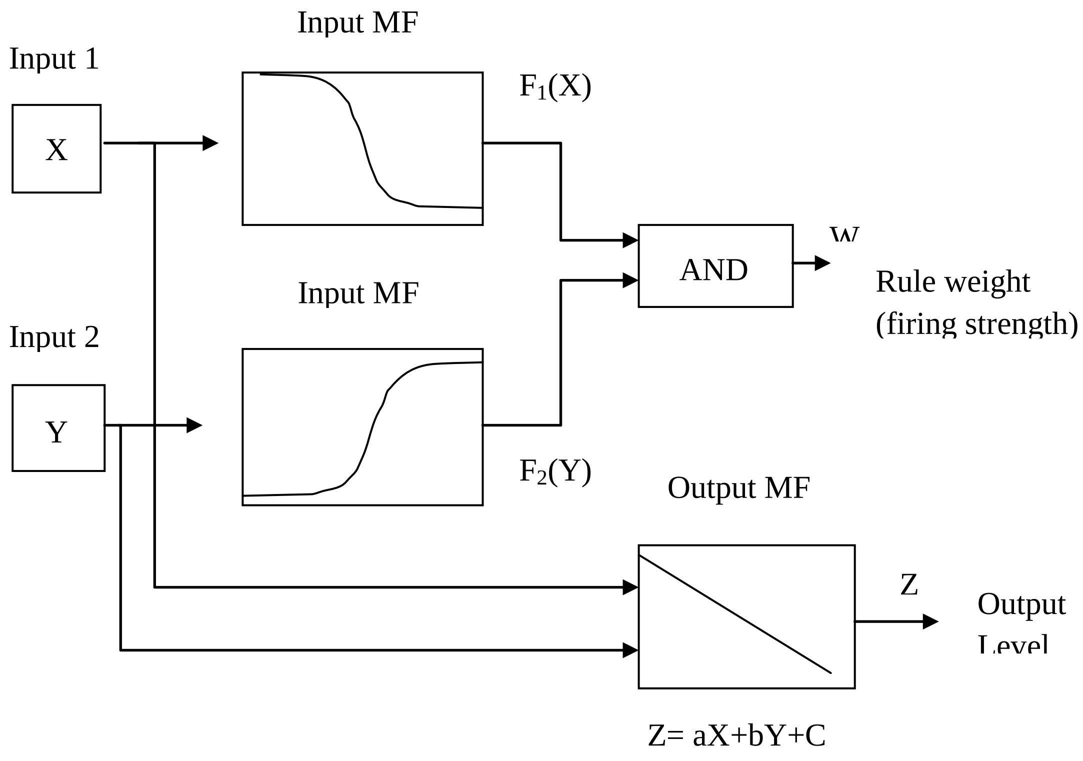

Figure 3. 4: Sugeno Rule

A typical rule in a Sugeno fuzzy model has the form

IF Input 1 = x AND Input 2 = y, THEN Output is z = ax + by + c.

For a zero-order Sugeno model, the output level zi a constant (a = b = 0).The output level z_i of each rule is weighted by the firing strength WI of the rule. For example, for an AND rule with Input 1 = x and Input 2 = y, the firing strength is

$$W_i = \text{And Method } (F_1(x), F_2(y)),$$

Where $F_{1,\,2}(\cdot)$ are the membership functions for Inputs 1 and 2. The final output of the system is the weighted average of all rule outputs, computed as

$$\text{Final output} = \frac{\sum_{i=1}^{N} wi\ zi}{\sum_{i=1}^{N} wi}$$

3.4 Introduction to ANFIS

ANFIS is one of the Neuro-fuzzy models. Neural networks and fuzzy systems both are stand-alone systems. With the increase in the complexity of the process being modelled, the difficulty in developing dependable fuzzy rules and membership functions increases. This has led to the development of another approach which is mostly known as ANFIS approach. It has the benefits of both neural networks and fuzzy logic. Some of the main disadvantages of fuzzy systems are that expert's knowledge or instructions are needed in order to define fuzzy rules, and that the process of tuning of the parameters of the fuzzy system (e.g. parameters of the membership functions) often requires a relatively long time. Both these disadvantages are related to the fact that it is not possible to train fuzzy systems. In order to compensate the disadvantages a hybrid system named ANFIS (Adaptive-Network-Based Fuzzy Inference System) has been proposed by Jang. Fuzzy inference in this system is realized with the aid of a training algorithm, which enables to tune the parameters of the fuzzy system.

3.5 ANFIS Architecture

The ANFIS is a fuzzy Sugeno model put in the framework of adaptive systems to facilitate learning and adaptation. The Sugeno fuzzy model was proposed by Takagi & Sugeno in an effort to formalize a systematic approach to generating fuzzy rules from an input-output data set.

A typical fuzzy rule in a Sugeno fuzzy model has the format

If x is A and y is B then z = f(x,y),

Where A , B are fuzzy sets in the antecedent; z = f(x, y) is a crisp function in the consequent.

Usually f(x, y) is a polynomial in the input variables x and y,but it can be any other functions that can appropriately describe the output of the system within the fuzzy region specified by the antecedent of the rule. If f(x, y) is a first-order polynomial, than model is called as the first-order Sugeno fuzzy model. If f is a constant, then it is called the zero-order Sugeno fuzzy model, which can be viewed either as a special case of the Mamdani fuzzy inference system, where each rule's consequent is specified by a fuzzy singleton, or a special case of Tsukamoto's fuzzy model where each rule's consequent is specified by a membership function of a step function centered at the constant. Moreover, a zero order Sugeno fuzzy model is functionally equivalent to a radial basis function network under certain minor constraints.

To facilitate the learning of the Sugeno fuzzy model, it is convenient to put the fuzzy model into framework of adaptive networks that can compute gradient vectors systematically. The resultant network architecture is ANFIS, which is shown in Figure-3.5, where node within the same layer performs functions of the same type, as detailed below. Here circle indicates a fixed node, whereas a square indicates an adaptive node.

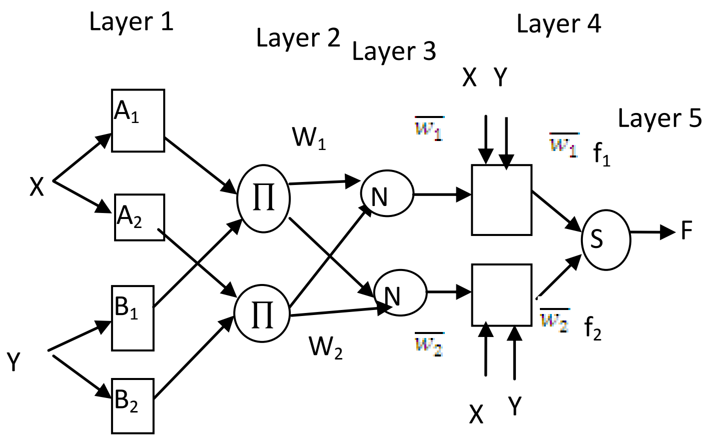

Figure 3. 5: ANFIS Architecture

Layer 1 Each node in this layer generates a membership grade of a linguistic label. For instance, the node function of the i_{th} node may be a generalized bell membership function:

$$O^1_i = \mu_{Ai}(x) = \frac{1}{1+((x-\frac{c_i}{a_i})^2)^{bi}} \qquad i=1, 2 \qquad (3.12)$$

where x is the input to node i; A_i is the linguistic label (small, large, etc.) associated with this node; and {ai, bi, ci} is the parameter set that changes the shapes of the membership function. Parameters in this layer are referred to as the premise parameters.

Layer 2 Each node in this layer calculates the firing strength of a rule via multiplication and the nodes are fixed:

$$O_i^2 = w_i = \mu_{Ai}(x)\ \mu_{Bi}(y), \qquad i=1, 2 \qquad (3.13)$$

Layer 3 The nodes are fixed nodes. They are labeled with *N*, indicating that they play a normalization role to the firing strengths from the previous layer. The outputs of this layer can be represented as:

$$O_i^3 = \overline{w}_i = \frac{w_i}{w_1+w_2}, \qquad i=1, 2 \qquad (3.14)$$

Layer 4 The nodes are adaptive nodes. The output of each node in this layer is simply the product of the normalized firing strength and a first-order polynomial (for a first-order Sugeno model). Thus, the outputs of this layer are given by:

$$O^4_i = \overline{w}_i f_i = \overline{w}_i(p_i x + q_i y + r_i) \qquad i= 1,2 \qquad (3.15)$$

Where $\overline{w}$ is the output of layer 3, and {p_i, q_i, r_i} is the parameter set. Parameters in this layer will be referred to as the consequent parameters.

Layer 5 There is only one single fixed node labelled with *S*. This node performs the summation of all incoming signals. Hence, the overall output of the model is given by:

$$O^5_i = \sum_{i=1}^{2} \overline{w}_i f_i = \frac{(\sum_{i=1}^{2} \overline{w}_i f_i)}{w_1+w_2} \qquad (3.16)$$

3.6 Conclusion

The tools of AI, such as neural networks and fuzzy logic, possess certain useful features such as nonlinearity, massive parallelism, learning capability, and human knowledge encoding capability. Fuzzy inference system is the most important modelling tool based on fuzzy set theory. The FISs are built by domain experts and are used in automatic control, decision analysis, and various other expert systems. In particular, this research uses a full-fledged fuzzy logic system proposed by Mamdani and Sugeno. Adaptive neuro fuzzy inference system (ANFIS) is also utilized in this research

Chapter-4
Fuzzy Assisted Handoff Algorithm

4.1 Introduction

In the reported work here we proposed a new (hard) handoff algorithm for both microcellular and macro cellular architecture with LOS (line of sight) transmission. In this chapter the design and analysis procedure for handoff algorithm is presented. A generalized frame work for the design of fuzzy logic based handoff algorithm is proposed and described. Different matrices that have been used to measure handoff related system performance are briefly touched upon here. Further more, ANFIS is applied for parameter adjustment to make the algorithm adaptive.

4.2 FLS Handoff Structure

The architecture of the proposed fuzzy algorithm is shown in Figure-4.1. Some of these modules collect the link and network layer information useful for handoff initiation. The FLS use this information to decide the appropriate time to initiate handoff.

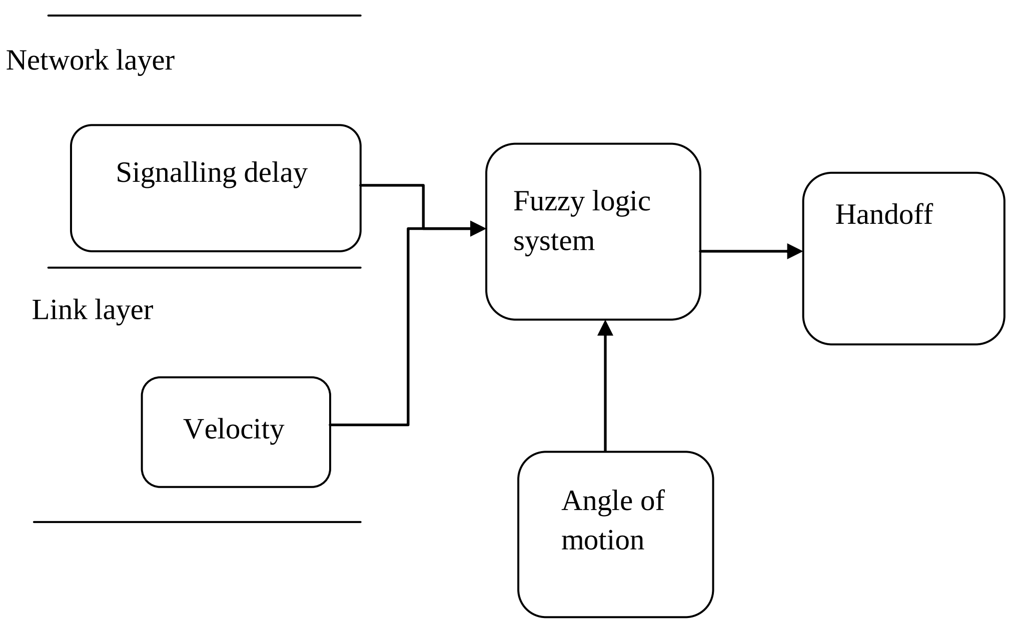

Figure 4. 1: Proposed Fuzzy Logic based Handoff Algorithm

The functionalites of these units are described as follows:

Signalling delay unit:

Information about velocity is collected from link layer and information about signalling delay is collected from Network layer. Signalling delay block in Figure-4.1 estimates the delay associated with handoffs. It is difficult to predict which particular BS the MT will move unless the handoff instance is very close. Our objective is to estimate the handoff signalling delay in advance without knowing which particular BS the MT will move. We used the technique proposed in [28] to estimate the delay. Estimating signalling delay in advance eliminates the adverse effect of parameters such as type of handoff, location of MT and load on network. Here we have taken the range of this input as 0- 2 second.

Velocity unit:

The most significant feature of mobile cellular system is that the users are moving. The velocity block of Figure-4.1estimates the velocity of mobile using VEPSD [29]. Doppler frequency (*fm*) is related to speed (*v*) of a mobile user, speed of light in free space (*c*), and carrier frequency of the received signal (*fc*) through

$$v = \left(\frac{c}{f_c}\right) f_m$$

VEPSD uses *fm* of received signal envelope to estimate speed of a mobile user. It estimates *fm* using the slope of power spectral density (PSD) of the received signal envelope. The slope of PSD of received signal envelope has maxima at frequencies $f_c \pm f_m$ in mobile environments. VEPSD detects the maximum value of received signal envelopes PSD that corresponds to the highest frequency component ($f_c + f_m$) to estimate f_m. Here we have taken velocity range from -100Km/h to +100Km/h, for macro cellular system and -15 Km/h to 15 Km/h for microcellular system. We have taken negative sign for, MT approaching the old base station and positive sign for moving away from it.

Angle of motion:

Referring to Figure-2.2 of chapter-2, during the course of movement of the MT let 'P' is the point where signal strength from BS1 is below the RSS threshold. Let 'P' be at a distance of'd' from the cell boundary and 'a' is the cell radius. When the MT is located at point P, it can move in any direction with equal probability. The need for handoff to BS2 arises only if MT's direction of motion from P is in the range [$\theta \in (-\theta_1, \theta_1)$], where θ_1=arc tan (a/2d). Otherwise, the handoff initiation is a false one. For macro cellular system we have taken a=1000m and d=100m, we calculate the range was -78^0 to $+78^0$. Similarly for microcellular system we have taken a=30m and d=1m and we calculate the range was -86^0 to $+86^0$. We have taken this parameter range from -180^0 to $+180^0$.

Finally the fuzzy logic unit process the input criteria and produces an output which is a membership value. This membership value represents the degree of handoff, which triggers the initiation of handoff.

4.3 Proposed Fuzzy Logic System

A fuzzy logic rule base is created based on the known sensitivity of handoff algorithm parameters. The operation of fuzzy logic system has been explained in chapter-3. We use FIS and ANFIS editor GUI (graphical user interface) of MATLAB for simulation. The membership function for input and output fuzzy variable is shown Figures-4.2-3.

The system has three iputs and one output.Each of the input is fuzzified at the input stage of FIS. The fuzzification process is presented in Figure-3.2 of chapter-3. Each input variable is categorised into 3 categories of fuzzy, "low", "medium" and "high". For input variable "velocity" the 3 catagories of fuzzy are "-ve", "NZ",(near zero) and "+ve". Therefore, the total numbers of rules for the fuzzy systems are 3×3×3=27. In this work we used both "Mamdani" and "Sugeno", fuzzy logic system. Triangular and trapezoidal membership functions with 50% overlap of assigned fuzzy sets were considered. Trapizoidal membership function is consider for edges andthe centre part is described using triangular membership function.The non-singelton fuzzifier and the centre of area (COA) de-fuzzification method are used for Mamdani model. Weighted average de-fuzzification method is used for Sugeno model. We used "AND" operator, "MIN" implication and "MAX" aggression method for both Mamdani and Sugeno model. The rules used in the proposed Mamdani FLS model were shown in the table-4.1. Similarl rules were defined for sugeno model as well. Resolving conflicting criteria in accordance with the global system goals is an important advantage of fuzzy logic. For example, consider rule 16 Signalling delay "high" encourages for handoff while "low" angle discourages the handoff. MTs velocity is neutral. Hence, the fuzzy logic rule makes the logical decision to keep handoff value medium. Results for the work is presented in chapter-5.

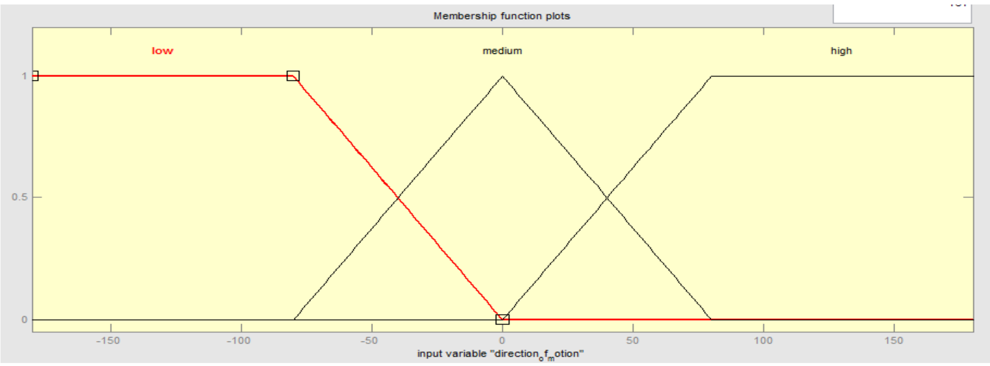

Figure 4. 2: Membership Function of Fuzzy Variable "Angle of Motion" (Mamdani System)

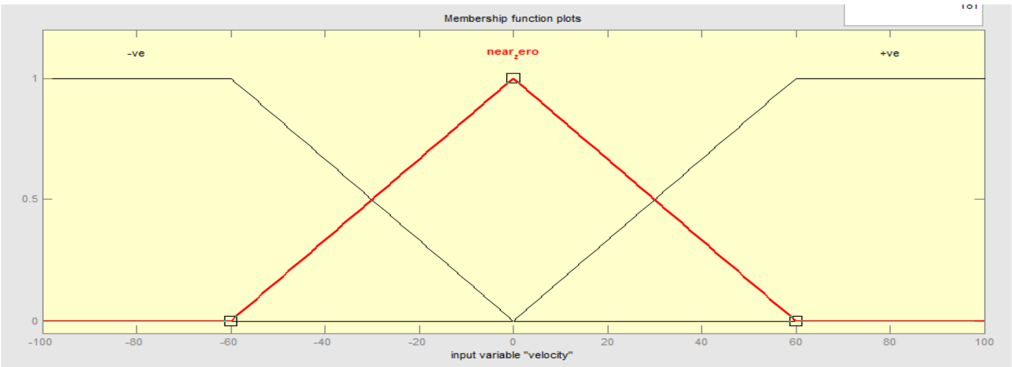

Figure 4. 3: Membership Function of Fuzzy Variable "Velocity" (Mamdani System)

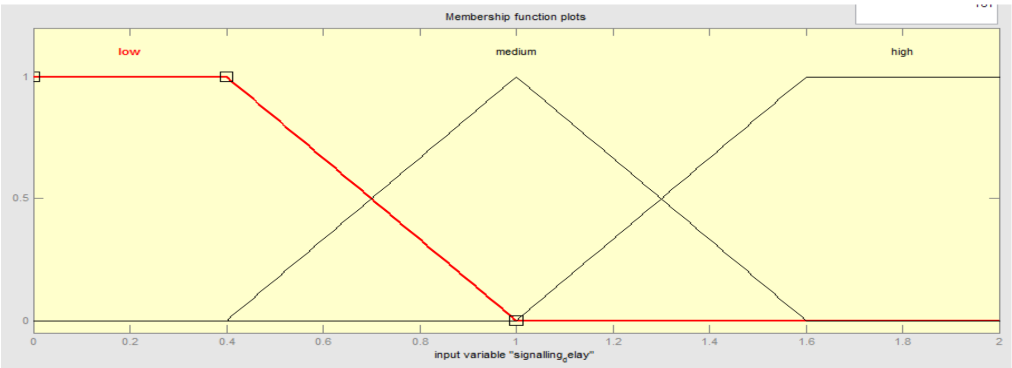

Figure 4. 4: Membership Function of Fuzzy Variable "Signalling Delay" (Mamdani System)

Table 5: Fuzzy Rule Base (Mamadani Model)

Rule no.	VELOCITY	SIGNALLING DELAY	ANGLE OF MOTION	HANDOFF
1	-VE	LOW	LOW	NO
2	-VE	LOW	MEDIUM	NO
3	-VE	LOW	HIGH	NO
4	-VE	MEDIUM	LOW	NO
5	-VE	MEDIUM	MEDIUM	MEDIUM
6	-VE	MEDIUM	HIGH	NO
7	-VE	HIGH	LOW	NO
8	-VE	HIGH	MEDIUM	YES
9	-VE	HIGH	HIGH	NO
10	NZ	LOW	LOW	NO
11	NZ	LOW	MEDIUM	MEDIUM
12	NZ	LOW	HIGH	NO
13	NZ	MEDIUM	LOW	MEDIUM
14	NZ	MEDIUM	MEDIUM	YES
15	NZ	MEDIUM	HIGH	MEDIUM
16	NZ	HIGH	LOW	MEDIUM
17	NZ	HIGH	MEDIUM	YES
18	NZ	HIGH	HIGH	MEDIUM
19	+VE	LOW	LOW	NO
20	+VE	LOW	MEDIUM	YES
21	+VE	LOW	HIGH	NO
22	+VE	MEDIUM	LOW	MEDIUM
23	+VE	MEDIUM	MEDIUM	YES
24	+VE	MEDIUM	HIGH	MEDIUM
25	+VE	HIGH	LOW	YES
26	+VE	HIGH	MEDIUM	YES
27	+VE	HIGH	HIGH	YES

In the work reported here the membership function was fixed and choosen by experts arbitrarily. The fuzzy rules were also choosen arbitrarily. Moreover the multiple parameters involved in proposed handoff decision algorithm increases the complexities of handoff process, making it slow and inefficient. This can be avoided if the parameters can be automatically adjusted depending on the data that was modeled. With this in mind

4.4 ANFIS for Handoff

Neuro-adaptive learning techniques provide a method for the fuzzy modeling procedure to learn information about a data set. Fuzzy Logic Toolbox software computes the membership function parameters that best allow the associated fuzzy inference system to track the given input/output data. Using a given input/output data set, the toolbox function anfis constructs a fuzzy inference system (FIS) whose membership function parameters are tuned (adjusted) using either a backpropagation algorithm alone or in combination with a least squares type of method. This adjustment allows the fuzzy systems to learn from the data they are modeling. The parameters associated with the membership functions changes through the learning process. The proposed algorithm uses ANFIS GUI of MATLAB for parameter adjustment. Figure-4.5 represents thes the ANFIS structure.

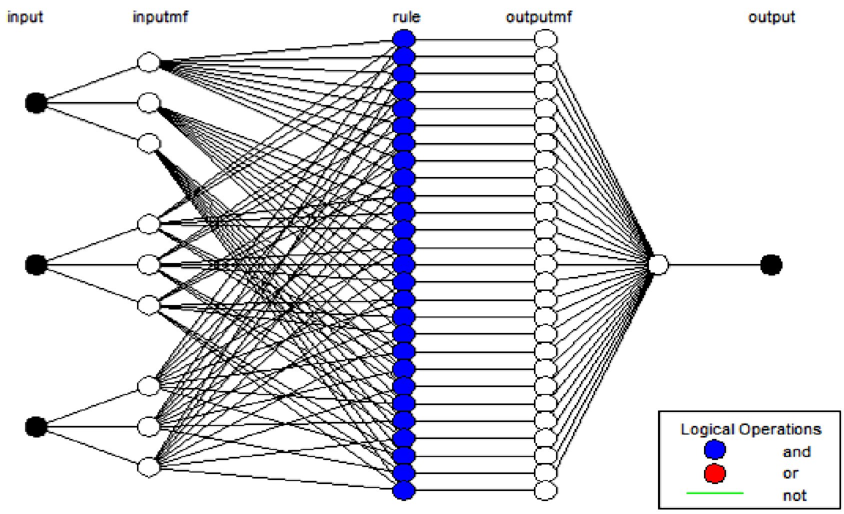

Figure 4. 5: ANFIS Structure

As shown in Figure-4.5 there are 3 inputs variables each having 3 membership functions. Therefore 27 rules were taken. The no of output membership functions are 27 and there is only one output. This is because ANFIS does not allow any rule sharing. To train the ANFIS 55 pairs of input output data were generated using the above discussed Mamdani system. Out of that 45 pairs are used for training and 10 pairs are used as checking data. There are two options available for designing a FIS in the ANFIS editor. They are [A] Grid partition method and [B] substractive clustering method. In this proposed work grid partition method is used. Hybrid algorithm is used for training the model. The model is then tested using training data set. Finally cheking datas are presented to the trained FIS model for validation, to see how well the FIS model predicts the corresponding data set output values. The details of ANFIS information, error plot, training and testing plots are shown and analyzed in chapter-5.

4.5 Conclusion

This chapter introduces a new class of handoff algorithms that exploits the knowledge of the working of several existing algorithms and uses fuzzy logic to adapt the parameters of handoff algorithms. A fuzzy logic rule base is created using the known sensitivities of handoff parameters. Furthermore, the proposed approach allows tuning of the FLS parameters using ANFIS to achieve a balanced trade-off among different system characteristics in the dynamic cellular environment. The design procedure for a generic fuzzy logic based algorithm is outlined.

Chapte-5
Result Discussion

5.1 Introduction

In this section simulation results for handoff with FIS and ANFIS is presented. The variation of handoff with reference to velocity and signalling delay are plotted. Performances in form of probability of false handoff initiation and handoff failure are considered. ANFIS is used to train the FIS for parameter adjustment and model validation.

5.2 Simulation model

For microcellular scenarios the simulation parameter considered are: cell size "a=30m" and the distance "d=1m". Maximum user velocity in microcellular system was considered to be 15 km/h. Similarly for macro cellular system "a =1km", "d = 100m" and a velocity of 100 km/h was considered.

5.3 Performance of Handoff with Signalling delay and Velocity (Mamdani)

The relationship of handoff with signalling delay and velocity are analyzed**.** Here Figure-5.1 shows the relationship of handoff with signalling delay when the serving BS belongs to a microcellular system. Similar results have been observed for macro cellular system. Figure-5.1 shows that handoff is increases as the signalling delay increases. This is because; the packets in transit can not be delivered to the MT during this high handoff latency period causing significant packet loss during handoff. So when signalling delay is high handoff must start earlier compared to when delay is small. Figure-5.2 presents variation of handoff against velocity. It is evident form Figur-5.2 that handoff increases as MTs speed increases. This implies that for a MT with high speed, the handoff initiation should start earlier compared to a slow moving MT. This can give guaranteed handoff before call drops leading to improvement in QOS.

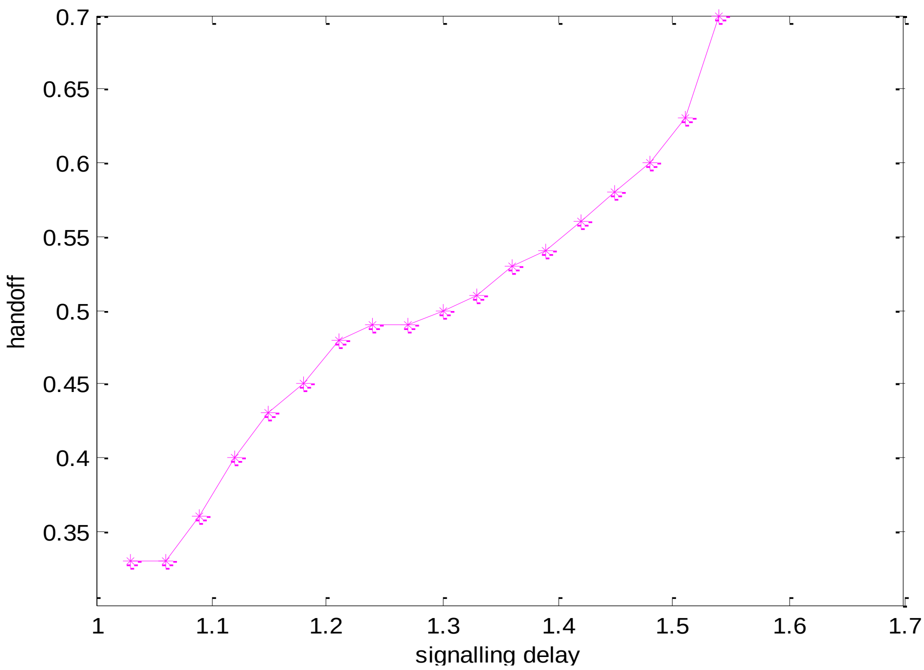

Figure5.1: Handoff for Different Signalling Delay (Microcellular System)

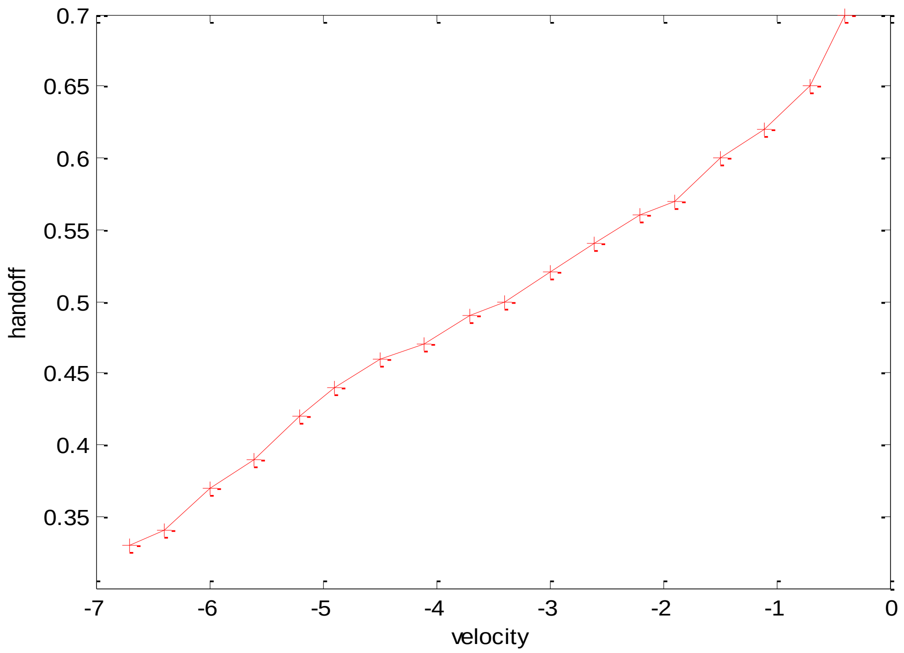

Figure5.2: Handoff for Different Velocity (Macro cellular system)

5.4 Relationship between False Handoff Probability (P_{fh}) and Velocity

Figure-5.3 and Figure-5.4 shows the comparison of the false handoff initiation probability (P_{fh}) of our new FLS with distance and velocity based FLS when the serving BS belongs to macro cellular and microcellular system respectively for fixed delay. The false handoff initiation probability of our new FLS is 10 percent to 17 percent less as compared to the distance based algorithm. Thus, FLS achieves up to 17% reduction in the cost associated with false handoff initiation. The use of adaptive *RSS* threshold initiates the handoff procedures in such a way that just enough time is there for the successful execution of the handoff. This avoids too early or too late initiation of the handoff process. The former limits the value of handoff failure probability. The later ensures that handoff is carried out smoothly. Thus, FLS optimizes the false handoff initiation probability and handoff failure probability.

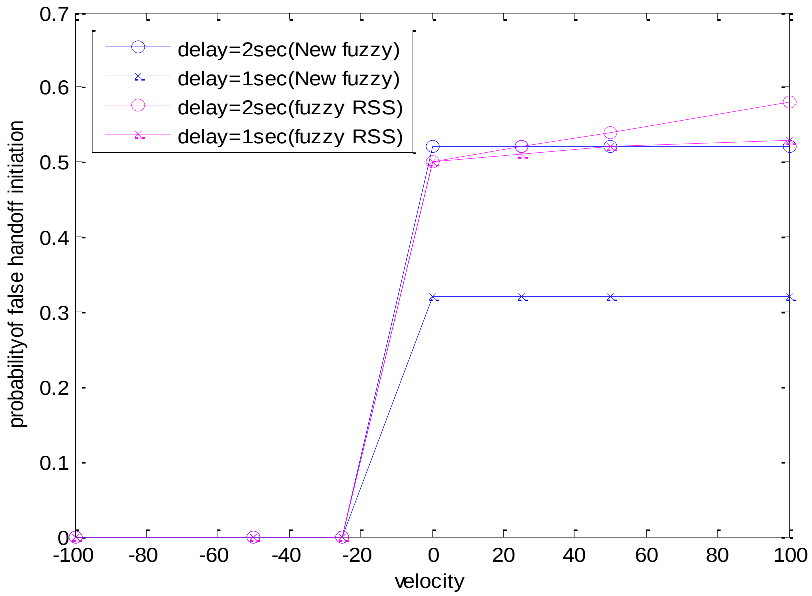

Figure 5.3: Relationship between False Handoff Initiation Probability and Velocity when BS belongs to a Macro cellular System for Fixed Delay

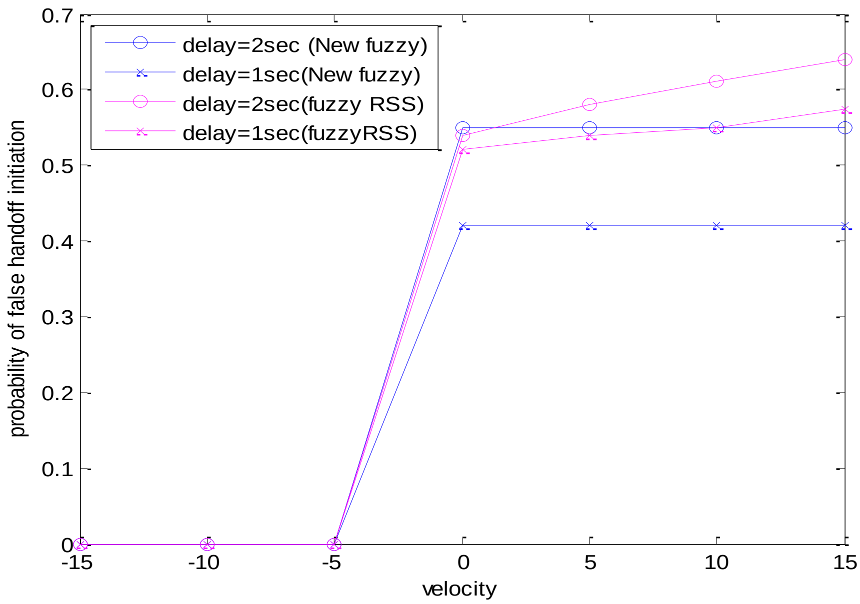

Figure 5.4: Relationship between Handoff Initiation Probability and Velocity when BS belongs to a Microcellular System for Fixed Delay

5.5 Relationship between Handoff Failure Probability (P_{hf}) and Velocity

Figure-5.5 and Figure 5.6 shows the handoff failure probability (P_{hf}) of FLS for different values of velocity when the serving BS belongs to a macro and micro-cellular system respectively.

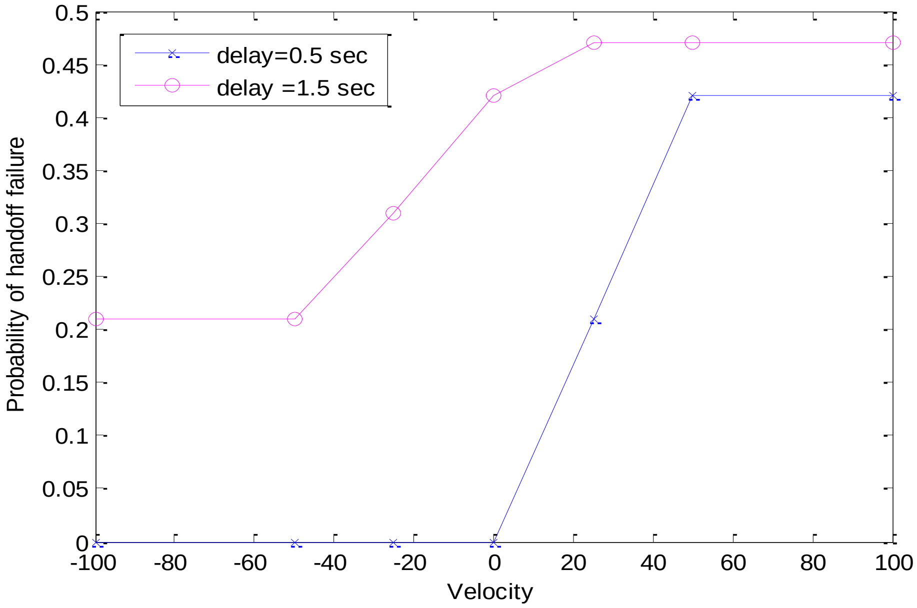

Figure5.5: Relationship between Handoff Failure Probability and Velocity when BS belongs to a Macro cellular System for Fixed Delay

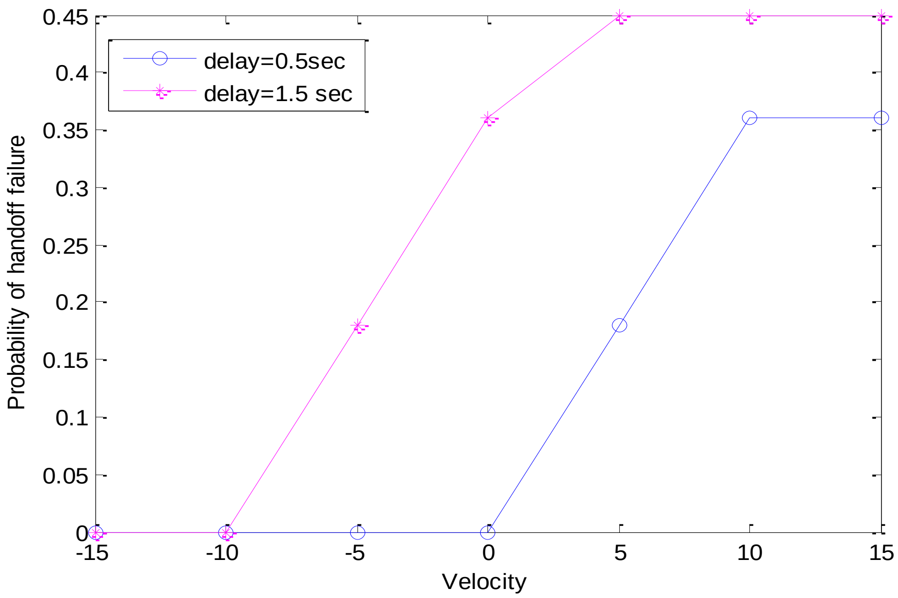

Figure5.6: Relationship between Handoff Failure Probability and Velocity when BS belongs to a Microcellular System for Fixed Delay

We Consider Delay of 0.5 sec for intra cellular and 1.5 sec for inter cellular handoff. These figures show that P_{hf} becomes higher for intersystem handoff compared to intrasystem handoff for a different speed. It also shows that there is a reduction of P_{hf} in micro-cellular system as compared to macro-cellular system. This indicates that number of handoff in micro-cellular system is more as compared to a macro cellular system. It is evident from Figures-5.5 and 5.6 that handoff failure probability increases with increasing the MTs speed. On the other hand, the P_{hf} increases with increasing signalling delay. This implies handoff initiation should start earlier at high value of signalling delay compared to low value of signalling delay.

5.6 Relationship between handoff failure probability and signalling delay

Figure-5.7 and Figure-5.8 shows the Comparison of handoff failure probability of new FLS with distance and velocity based FLS algorithm when the serving BS belongs to micro cellular system and macrocellular system. The result shows that handoff failure probability is independent of Signalling delay in distance and velocity based FLS, because it considers signalling delay for tuning membership function. But in the proposed FLS, results show that there is increase in probability of handoff with increase in signalling delay. Also it is evident from the Figure-5.7 that, with increasing signalling delay, the handoff failure probability decreases when the MT is approaching the serving BS. This implies that more number of handoffs is performed near the cell boundary. We got similar results for macro-cellular system represented in Figure-5.8. The probability of handoff failure is more in macrocellular system then microcellular system. Also from these figures the higher values of delay correspond to intersystem handoff scenarios and the lower values of delay correspond to intrasystem handoff scenarios. Therefore, to keep the handoff failure probability limited, it is essential to predict handoff signaling delay in advance

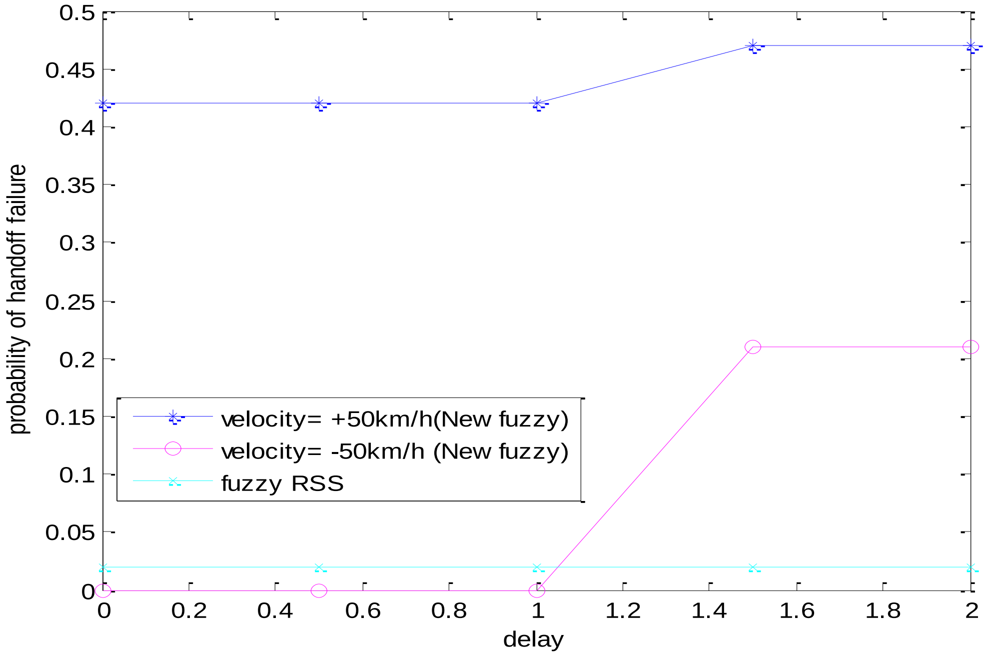

Figure 5.7: Relationship between Handoff Failure Probability and Delay when BS belongs to a Micro cellular System for Fixed Velocity

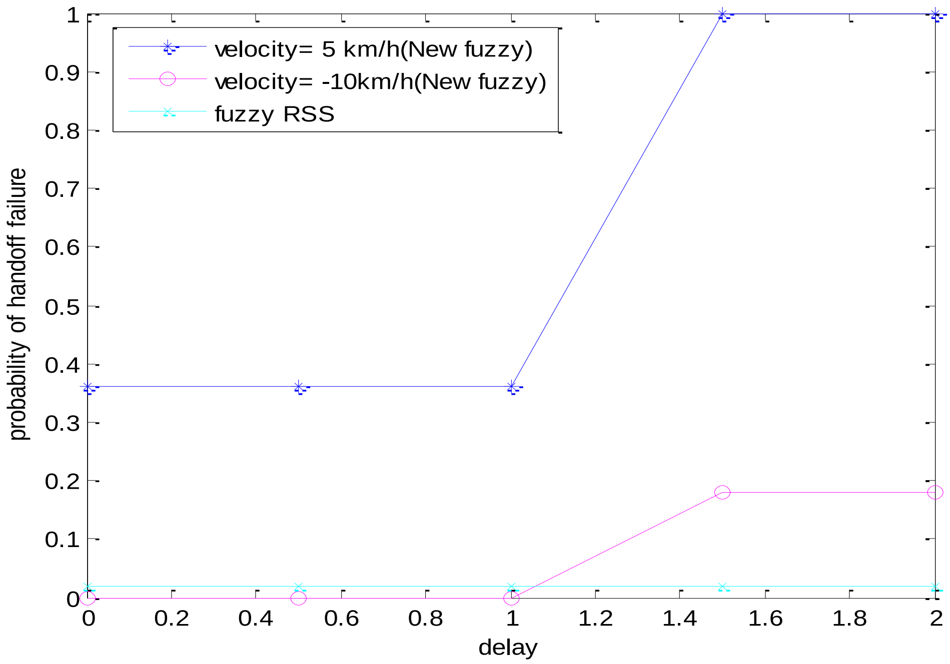

Figure 5.8: Relationship between Handoff Failure Probability and Delay when BS belongs to a Macrocellular System for Fixed Velocity

5.7 Sugeno Output

The simulation results for handoff in case of Sugeno model is analyzed below.The results shown are clearly able to describe the intercellular and intra cellular handoff. Figure-5.11 represents the surface plot of handoff against velocity and Signalling delay of MT. From Figure-5.11, it is evident that the handoff is low when the MT approaching the serving BS. The value of handoff is high for high velocity and signalling delay. This can be cosnidered as intercellular handoff. Similarly for medium value of velocity and signalling delay the handoff is high. This can be considered as intra cellular handoff. Figure-5.12 represents the surface plot of handoff with respect to angle of motion and signalling delay of MT.

In this figure, handoff increase with increaseing signalling delay. For the calculated value of signalling delay (refer chapter-4) high handoff can be considered as inter cellular handoff. Other than the calculated range ($\pm 78^0$ for macro and $\pm 86^0$ for micro cellular) the handoff is also high for high signalling delay which can be reffered as intra cellular handoff.

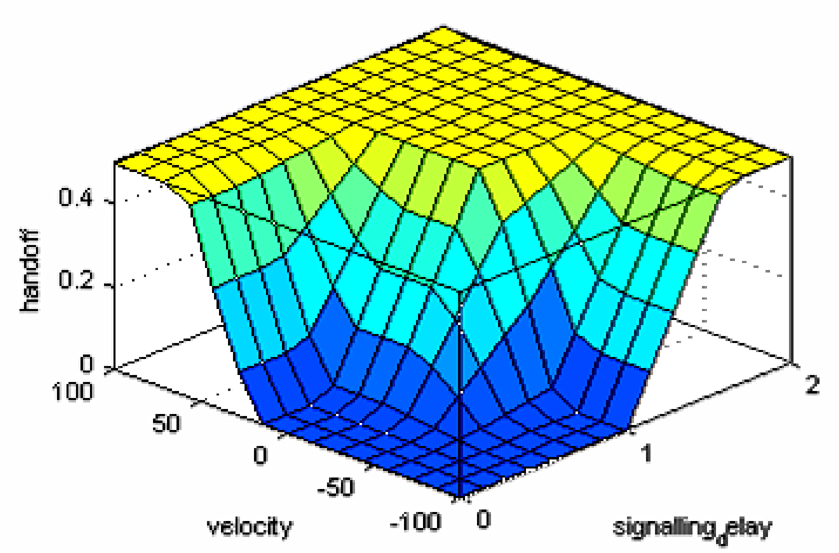

Figure 5.9: Surface plot of Handoff vs Signalling Delay and Velocity

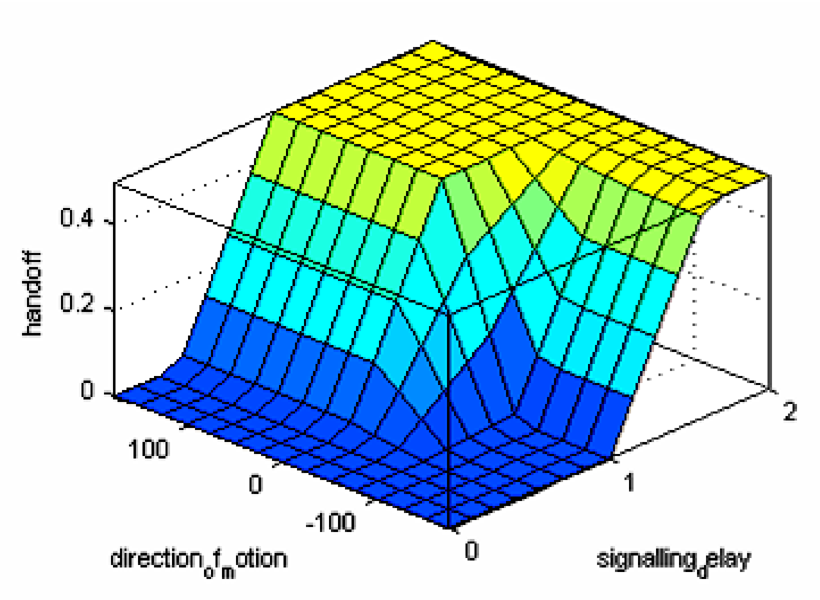

Figure 5.10: Surface plot of Handoff vs. Signalling Delay and Angle of Motion

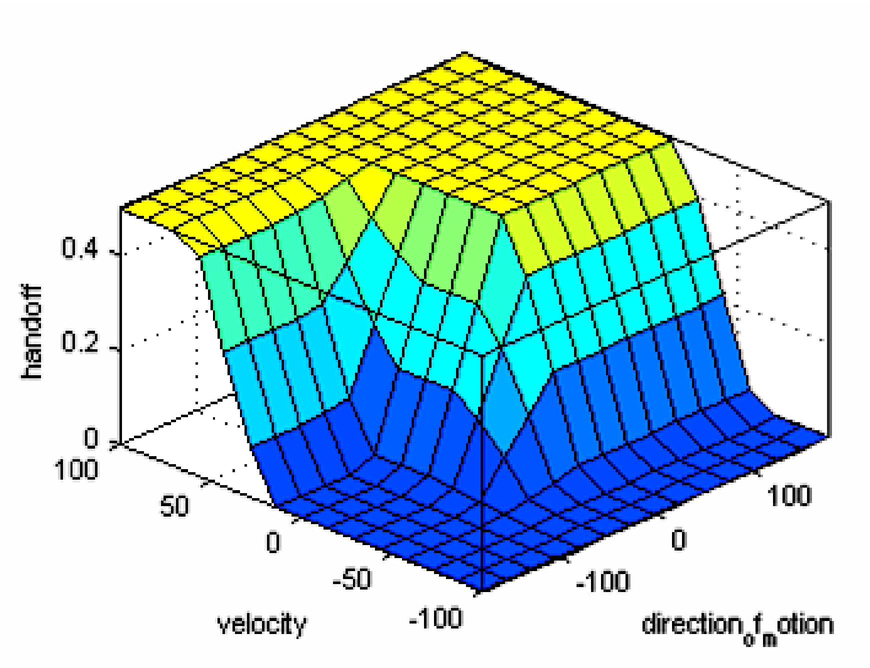

Figure 5.11: Surface plot of Handoff vs. Angle of Motion and Velocity

Figure 5.13represents the surface plot of handoff against angle of motion and velocity of MT. It impliest that when MT is moving away from the serving BS with high velocity the handoff increases whatever may be the value of angle of motion.

5.8 ANFIS Output

In above discussed Sugeno model, we used trapezoidal membership function with three fuzzy sets for each input variable. In this section the Sugeno model is trained with known input /output data set. We generate 80 data pairs using Mamdani model discussed in chapter-5 to tune the Sugeno model. The first 45 pairs used for training, last 10 pairs used for checking and the rest 5 pairs with another 5 pair from training data were used for testing data. With the following ANFIS information given in Table-6, the training error plot is shown in Figure-5.14. The model is validated using 10 number of checking data pairs, to see how well the FIS model predicts the corresponding data set output values. Here two similar data sets are used for training and checking, but the checking data set is corrupted by a small amount of noise. Figure-5.15 and 5.16 represents the FIS output after testing with training and checking data respectively.

Table 6: ANFIS Information (trapizoidal membership function)

Learning Algorithm	Hybrid
No.of Nodes	78
Error Tolerence	0
No.of Epoches	20
No. of Linear parameter	27
No. of Non- Linear parameter	36
Total No. Of parameter	63
No.of Training data pairs	45
No.of Checking data pairs	10
No.of Rules	27

The idea behind using a checking data set for model validation is that after a certain point in the training, the model begins over fitting the training data set. The model error for the checking data set tends to decrease as the training takes place up to the point that over fitting begins, and then the model error for the checking data suddenly increases. Over fitting is accounted for by testing the FIS trained on the training data against the checking data, and choosing the membership function parameters to be those associated with the minimum checking error if these errors indicate model over fitting.

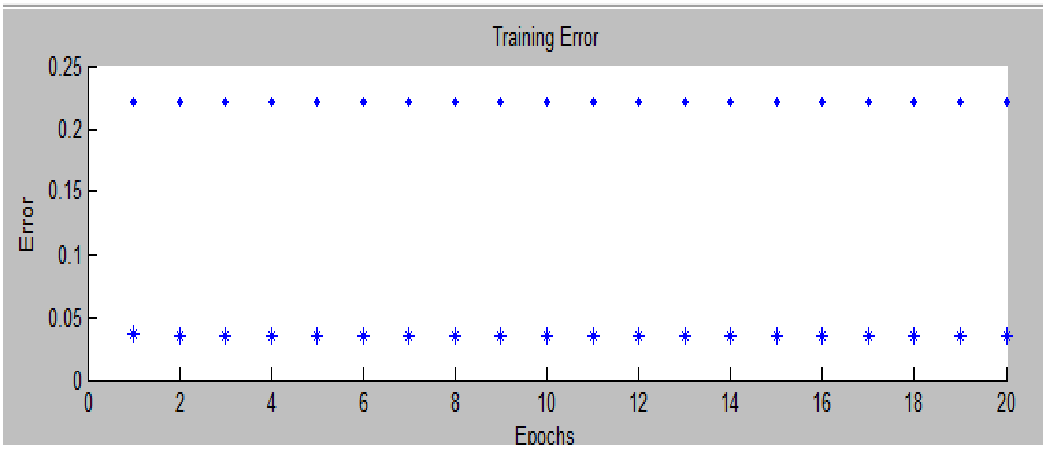

Figure5. 12: Error plot after Training

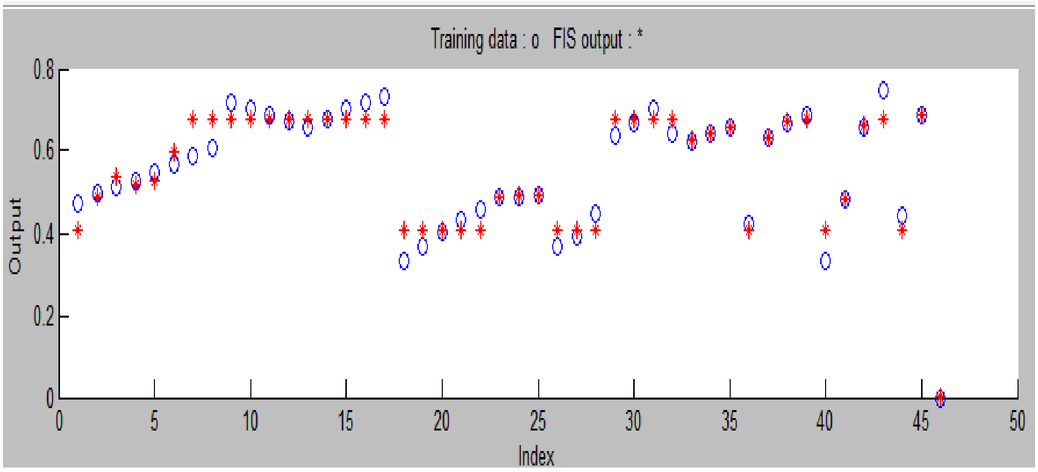

Figure5.13: FIS output after Testing with Training Data

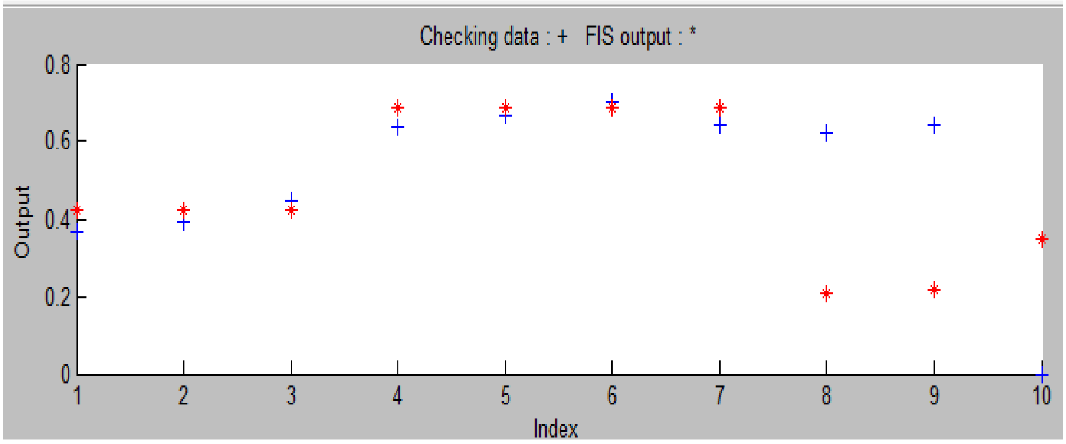

Figure5.14: FIS output after Testing with Checking Data

The error plot in Figure-5.14 does not showing the point of over fitting. This is due to less number of input/output data set. But Figure-5.15 clearly implies that the model has not been trained well as many of the output data points are not matching with the trained data.

Similarly in Figure-5.16 there is a mismatch of about 40% between output and checking data. In general the testing performance tells that the model doesn't learn what it supposed to learn

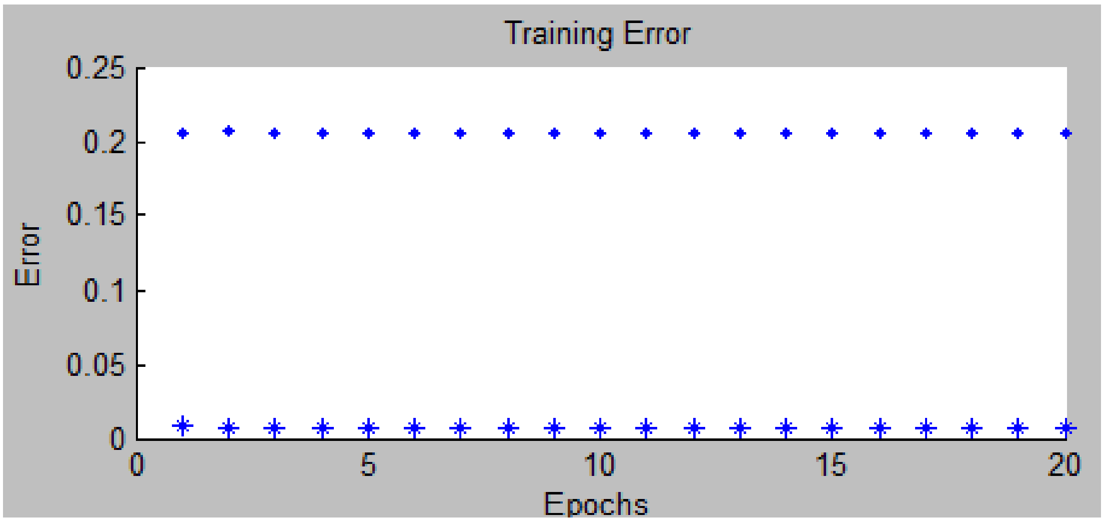

Figure5.15: Error plot with Gaussian Membership Function

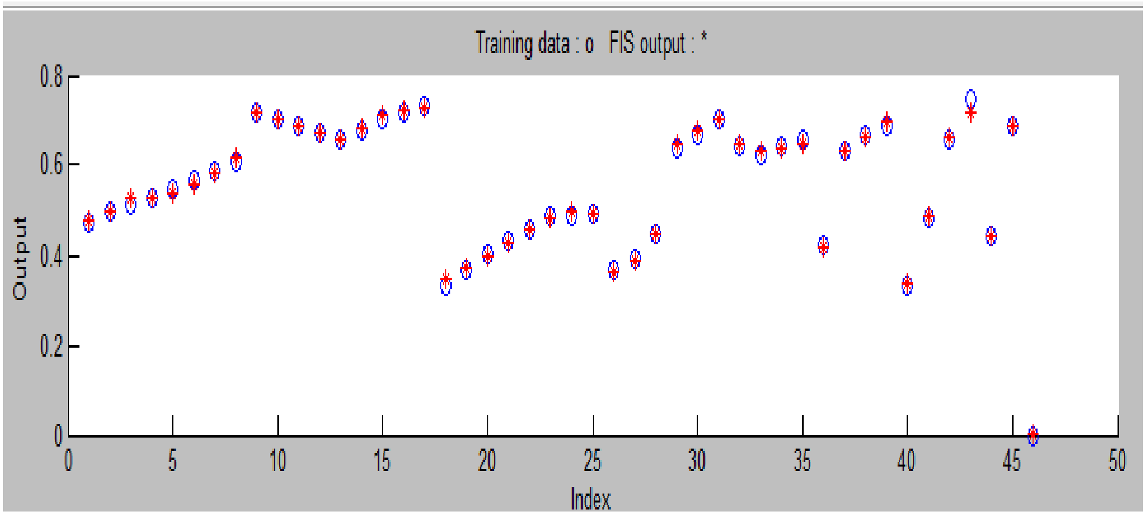

Figure 5. 16: FIS output after testing with Training Data (Gaussian Membership Function)

Error can be reduced in two ways; [A] the number of selected data point for training should be more or [B] it may need to modify the membership function (both shape and type). Since data points are selected from Mamdani model, so it is difficult to select more data points because of chance of rule sharing. Therefore, we change the type of membership function. ANFIS GUI of MATLAB provides 8 types of membership function. After tested with each of those membership functions, we found that Gaussian membership function provides lowest training error. This is because Gaussian membership function has lowest tuneable parameter. So the number of modifiable parameter decreases. Also the noise in general is Gaussian in all communication system, so using Gaussian membership function best approximate the model. Table-7 shows Anfis information for Gaussian membership function. From Table-7 it is clear that using Gaussian membership function decrease the number of nonlinear parameter from 36 to 18 (compared to Table-6). This leads to increase in training data set over modifiable parameter. Figure-5.17 shows the error plots. Figure-5.18 and5.19 represents the FIS output after testing with training and checking data respectively (for Gaussian membership function).

Table 7: ANFIS Information (Gaussian Membership function)

Learning Algorithm	Hybrid
No.of Nodes	78
Error Tolerence	0
No.of Epoches	20
No. of Linear parameter	27
No. of Non- Linear parameter	18
Total No. Of parameter	45
No.of Training data pairs	45
No.of Checking data pairs	10
No.of Rules	27

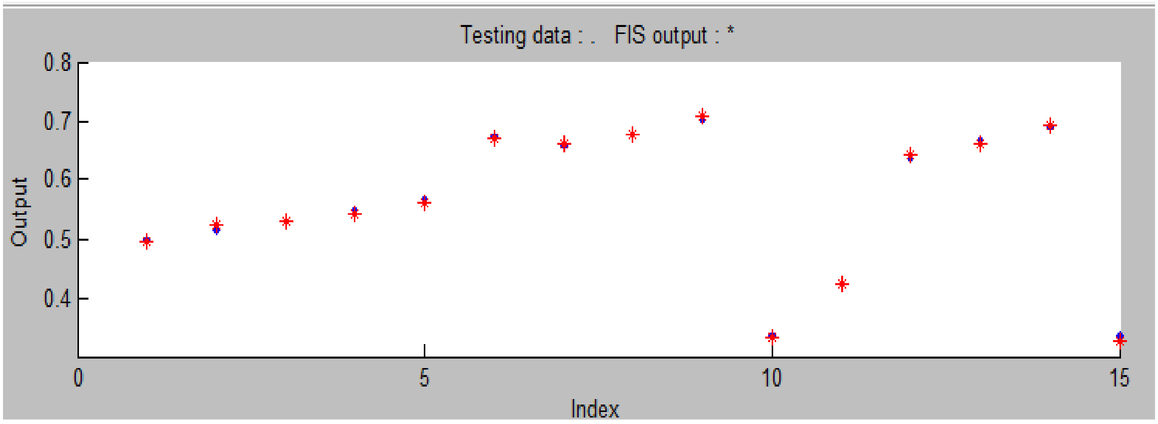

Figure 5.17: FIS output after Testing with Training Data

5.9 Conclusion

This chapter briefly describes the simulation results of Mamdani and Sugeno model. The variation of handoff with respect to varying signalling delay and velocities were analyzed. Handoff performances matrices, such as false handoff initiation probability and handoff failure probability for both micro-cellular and macro-cellular architecture were analyzed. These results are in coincidence with the results obtained by analytical solution. Sugeno model is trained using ANFIS with known set of input/output data for parameter adjustment. Result shows that training with Gaussian membership function decreases the error and make the system learn what it suppose to learn.

Chapter-6
Conclusion and Future work

6.1 Conclusion

This chapter summarizes the dissertation research and discusses potential directions for future research in the area.

Thesis Contribution

Handoff is an integral component of cellular communications. The handoff process determines the spectral efficiency and the quality perceived by users. Many of the existing handoff algorithms do not exploit advantages of multi-criteria handoff. In this research a new fuzzy logic based hard handoff algorithm for micro and macro cellular architecture is introduced. A fuzzy logic rule base is created using the known sensitivities of handoff parameters. It uses mobile's speed, direction of motion and signalling delay information to enhance the performance of handoff initiation significantly. It also significantly reduces the cost associated with the false handoff initiation because it achieves lower false handoff initiation probability than existing handoff algorithms. Furthermore, the proposed approach allows tuning of the FLS parameters to achieve a balanced tradeoff among different system characteristics in the dynamic cellular environment.

Chapter 2 discusses different aspects of handoff and provides a literature survey of handoff related research work. The contents of this chapter are extremely valuable since the full potential of any new approaches for an efficient handoff process cannot be realized without the essential knowledge about the cellular system and the response of the cellular system to different handoff parameters.

Chapter 3 introduces two major tools of AI that are utilized in this research. Background information on fuzzy logic and ANFIS is given. These tools provide an efficient and convenient architecture to represent the designer's knowledge about the system and its environment.

Chapter 4 outlines the design procedure of proposed handoff algorithm.The handoff algorithm has been improved by considering two new parameter, signalling delay and angle of motion of MT along with velocity as input criteria. The proposed fuzzy inference scheme uses triangular and trapezoidal membership function for fuzzification. The types of defuzzification method used are centroid and weighted average formula for Mamdani and Sugeno model respectively. Extensive simulation analysis has been used to validate the proposed technique

Chapter 5 describes the simulation results of Mamdani and Sugeno model. The variation of handoff with respect to varying signalling delay and velocities were analyzed. Handoff performances matrices, such as false handoff initiation probability and handoff failure probability for both micro-cellular and macro-cellular architecture were analyzed. These results are in coincidence with the results obtained by analytical solution. Sugeno model is trained using ANFIS with known set of input/output data for parameter adjustment. Result shows that training with Gaussian membership function decreases the error and make the system learn what it suppose to learn.

This work can be extended in several directions as described next.

6.2 Scope of Future Work

Algorithm Study

This dissertation focuses on fuzzy assisted handoff algorithms. Some of the other potential new classes of algorithms capable of providing high performance may include prediction based algorithms and self-tuning algorithms.

Application Study

The proposed algorithms can serve as a basis to obtain high performance algorithms for other architetures such as overlay architecture, femto cell structure, sattelite based communication systems and next genaration communication systems.

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